Refine Search

Search Results -

Terms	Documents
monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	3

Database:
US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search: L3

Refine Search

Recall Text Clear Interrupt

Search History

DATE: Monday, August 01, 2005 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L3	monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	3	L3
L2	L1 and monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	0	L2
L1	706/21.ccls.	177	L1

END OF SEARCH HISTORY

Hit List

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs
Generate OACS

Search Results - Record(s) 1 through 3 of 3 returned.

☐ 1. Document ID: US 20040082438 A1

L3: Entry 1 of 3 File: PGPB Apr 29, 2004

PGPUB-DOCUMENT-NUMBER: 20040082438
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20040082438 A1

TITLE: Method and apparatus for speed controlled eccentric exercise training

PUBLICATION-DATE: April 29, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
LaStayo, Paul	Salt Lake City	UT	US	
Lindstedt, Stan	Flagstaff	AZ	US	
Hoppeler, Hans	Bolligen	CO	CH	
Madden, Henry	Boulder	CO	US	
Estoque, Daniel A.	Boulder	CO	US	
Stephens, William B.	Boulder	CO	US	
Volan, Gregory D.	Longmont		US	

US-CL-CURRENT: 482/8; 482/57, 482/63

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

☐ 2. Document ID: US 5751910 A

L3: Entry 2 of 3 File: USPT May 12, 1998

US-PAT-NO: 5751910
DOCUMENT-IDENTIFIER: US 5751910 A
**** See image for Certificate of Correction ****

TITLE: Neural network solder paste inspection system

DATE-ISSUED: May 12, 1998

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Bryant; Steven M.	Holley	NY		
Loewenthal; Kenneth H.	Reston	VA		

US-CL-CURRENT: 706/2; 382/145, 382/147, 382/157, 382/159, 706/16, 706/23, 706/912

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

3. Document ID: US 5486998 A

L3: Entry 3 of 3 File: USPT Jan 23, 1996

US-PAT-NO: 5486998
DOCUMENT-IDENTIFIER: US 5486998 A

TITLE: Process stabilizing process controller

DATE-ISSUED: January 23, 1996

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Corso; Ronald	Indianapolis	IN		

US-CL-CURRENT: 700/32; 706/23

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs | Generate OACS

Terms	Documents
monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	3

Display Format: - Change Format

Previous Page Next Page Go to Doc#

Refine Search

Search Results -

Terms	Documents
L1 and coefficients and radial near basis and neural	10

Database:
US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search: L4

Refine Search

Recall Text Clear Interrupt

Search History

DATE: Monday, August 01, 2005 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L4	L1 and coefficients and radial near basis and neural	10	L4
L3	monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	3	L3
L2	L1 and monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	0	L2
L1	706/21.ccls.	177	L1

END OF SEARCH HISTORY

Hit List

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs | Generate OACS

Search Results - Record(s) 1 through 10 of 10 returned.

☐ 1. Document ID: US 20050114279 A1

L4: Entry 1 of 10 File: PGPB May 26, 2005

PGPUB-DOCUMENT-NUMBER: 20050114279
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20050114279 A1

TITLE: Development of electronic employee selection systems and methods

PUBLICATION-DATE: May 26, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Scarborough, David J.	West Linn	OR	US	
Chambless, Bjorn	Portland	OR	US	
Becker, Richard W.	Portland	OR	US	
Check, Thomas F.	Beaverton	OR	US	
Clainos, Deme M.	Lake Oswego	OR	US	
Eng, Maxwell W.	Portland	OR	US	
Levy, Joel R.	Portland	OR	US	
Mertz, Adam N.	Portland	OR	US	
Paajanen, George E.	West Linn	OR	US	
Smith, David R.	Beaverton	OR	US	
Smith, John R.	Hillsboro	OR	US	

US-CL-CURRENT: 706/21; 705/1

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

☐ 2. Document ID: US 20040059694 A1

L4: Entry 2 of 10 File: PGPB Mar 25, 2004

PGPUB-DOCUMENT-NUMBER: 20040059694
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20040059694 A1

TITLE: Method and apparatus for providing a virtual age estimation for remaining lifetime prediction of a system using neural networks

PUBLICATION-DATE: March 25, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Darken, Christian J.	Carmel Valley	CA	US	
Loecher, Markus	Princeton Jct.	NJ	US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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3. Document ID: US 20030191728 A1

L4: Entry 3 of 10 File: PGPB Oct 9, 2003

PGPUB-DOCUMENT-NUMBER: 20030191728
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20030191728 A1

TITLE: Performance of artificial neural network models in the presence of instrumental noise and measurement errors

PUBLICATION-DATE: October 9, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Kulkarni, Bhaskar Dattatray	Pune		IN	
Tambe, Sanjeev Shrikrishna	Pune		IN	
Lonari, Jayaram Budhaji	Pune		IN	
Valecha, Neelamkumar	Mumbai		IN	
Dheshmukh, Sanjay Vasantrao	Mumbai		IN	
Shenoy, Bhavanishankar	Mumbia		IN	
Ravichandran, Sivaraman	Mumbai		IN	

US-CL-CURRENT: 706/21; 706/31

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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4. Document ID: US 20030140023 A1

L4: Entry 4 of 10 File: PGPB Jul 24, 2003

PGPUB-DOCUMENT-NUMBER: 20030140023
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20030140023 A1

TITLE: System and method for pre-processing input data to a non-linear model for use in electronic commerce

PUBLICATION-DATE: July 24, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Ferguson, Bruce	Round Rock	TX	US	
Hartman, Eric	Austin	TX	US	

US-CL-CURRENT: 706/21; 706/15

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KMC | Draw De

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5. Document ID: US 20030078901 A1

L4: Entry 5 of 10 File: PGPB Apr 24, 2003

PGPUB-DOCUMENT-NUMBER: 20030078901
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20030078901 A1

TITLE: Neural network based predication and optimization for groundwater / surface water system

PUBLICATION-DATE: April 24, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Coppola, Emery J. JR.	Lawrenceville	NJ	US	
Poulton, Mary M.	Tucson	AZ	US	
Szidarovszky, Ferenc			US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KMC | Draw De

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6. Document ID: US 20020046199 A1

L4: Entry 6 of 10 File: PGPB Apr 18, 2002

PGPUB-DOCUMENT-NUMBER: 20020046199
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20020046199 A1

TITLE: Electronic employee selection systems and methods

PUBLICATION-DATE: April 18, 2002

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Scarborough, David J.	West Linn	OR	US	
Chambless, Bjorn	Portland	OR	US	
Becker, Richard W.	Portland	OR	US	
Check, Thomas F.	Beaverton	OR	US	
Clainos, Deme M.	Lake Oswego	OR	US	

Eng, Maxwell W.	Portland	OR	US
Levy, Joel R.	Portland	OR	US
Mertz, Adam N.	Portland	OR	US
Paajanen, George E.	West Linn	OR	US
Smith, David R.	Beaverton	OR	US
Smith, John R.	Hillsboro	OR	US

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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☐ 7. Document ID: US 20020042786 A1

L4: Entry 7 of 10 File: PGPB Apr 11, 2002

PGPUB-DOCUMENT-NUMBER: 20020042786
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20020042786 A1

TITLE: Development of electronic employee selection systems and methods

PUBLICATION-DATE: April 11, 2002

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Scarborough, David J.	West Linn	OR	US	
Chambless, Bjorn	Portland	OR	US	
Becker, Richard W.	Portland	OR	US	
Check, Thomas F.	Beaverton	OR	US	
Clainos, Deme M.	Lake Oswego	OR	US	
Eng, Maxwell W.	Portland	OR	US	
Levy, Joel R.	Portland	OR	US	
Mertz, Adam N.	Portland	OR	US	
Paajanen, George E.	West Linn	OR	US	
Smith, David R.	Beaverton	OR	US	
Smith, John R.	Hillsboro	OR	US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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☐ 8. Document ID: US 6879971 B1

L4: Entry 8 of 10 File: USPT Apr 12, 2005

US-PAT-NO: 6879971
DOCUMENT-IDENTIFIER: US 6879971 B1

TITLE: Automated method for building a model

DATE-ISSUED: April 12, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Keeler; James D.	Austin	TX		
Hartman; Eric J.	Austin	TX		
Godbole; Devendra B.	Austin	TX		
Piche; Steve	Austin	TX		
Arbila; Laura	Austin	TX		
Ellinger; Joshua	Austin	TX		
Ferguson, II; R. Bruce	Round Rock	TX		
Krauskop; John	Austin	TX		
Kempf; Jill L.	Austin	TX		
O'Hara; Steven A.	Round Rock	TX		
Strauss; Audrey	Austin	TX		
Telang; Jitendra W.	Austin	TX		

US-CL-CURRENT: 706/21; 706/15, 706/23, 706/903, 706/906, 706/907

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

9. Document ID: US 6647377 B2

L4: Entry 9 of 10 File: USPT Nov 11, 2003

US-PAT-NO: 6647377
DOCUMENT-IDENTIFIER: US 6647377 B2

TITLE: Multi-kernel neural network concurrent learning, monitoring, and forecasting system

DATE-ISSUED: November 11, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Jannarone; Robert J.	Atlanta	GA		

US-CL-CURRENT: 706/16; 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

10. Document ID: US 6243696 B1

L4: Entry 10 of 10 File: USPT Jun 5, 2001

US-PAT-NO: 6243696
DOCUMENT-IDENTIFIER: US 6243696 B1

TITLE: Automated method for building a model

DATE-ISSUED: June 5, 2001

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Keeler; James D.	Austin	TX		
Hartman; Eric J.	Austin	TX		
Godbole; Devendra B.	Austin	TX		
Piche; Steve	Austin	TX		
Arbila; Laura	Austin	TX		
Ellinger; Joshua	Austin	TX		
Ferguson, II; R. Bruce	Round Rock	TX		
Krauskop; John	Austin	TX		
Kempf; Jill L.	Austin	TX		
O'Hara; Steven A.	Round Rock	TX		
Strauss; Audrey	Austin	TX		
Telang; Jitendra W.	Austin	TX		

US-CL-CURRENT: 706/21; 706/906, 706/907

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs | Generate OACS

Terms	Documents
L1 and coefficients and radial near basis and neural	10

Display Format: - Change Format

Previous Page Next Page Go to Doc#

Refine Search

Search Results -

Terms	Documents
L4 and predict$5 and train$5	10

Database:

US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search: L5

Refine Search

Recall Text Clear Interrupt

Search History

DATE: Monday, August 01, 2005 Printable Copy Create Case

Set Name side by side	**Query**	**Hit Count**	**Set Name** result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L5	L4 and predict$5 and train$5	10	L5
L4	L1 and coefficients and radial near basis and neural	10	L4
L3	monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	3	L3
L2	L1 and monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	0	L2
L1	706/21.ccls.	177	L1

END OF SEARCH HISTORY

Hit List

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs
Generate OACS

Search Results - Record(s) 1 through 10 of 10 returned.

☐ 1. Document ID: US 20050114279 A1

L5: Entry 1 of 10 File: PGPB May 26, 2005

PGPUB-DOCUMENT-NUMBER: 20050114279
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20050114279 A1

TITLE: Development of electronic employee selection systems and methods

PUBLICATION-DATE: May 26, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Scarborough, David J.	West Linn	OR	US	
Chambless, Bjorn	Portland	OR	US	
Becker, Richard W.	Portland	OR	US	
Check, Thomas F.	Beaverton	OR	US	
Clainos, Deme M.	Lake Oswego	OR	US	
Eng, Maxwell W.	Portland	OR	US	
Levy, Joel R.	Portland	OR	US	
Mertz, Adam N.	Portland	OR	US	
Paajanen, George E.	West Linn	OR	US	
Smith, David R.	Beaverton	OR	US	
Smith, John R.	Hillsboro	OR	US	

US-CL-CURRENT: 706/21; 705/1

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

☐ 2. Document ID: US 20040059694 A1

L5: Entry 2 of 10 File: PGPB Mar 25, 2004

PGPUB-DOCUMENT-NUMBER: 20040059694
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20040059694 A1

TITLE: Method and apparatus for providing a virtual age estimation for remaining lifetime prediction of a system using neural networks

PUBLICATION-DATE: March 25, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Darken, Christian J.	Carmel Valley	CA	US	
Loecher, Markus	Princeton Jct.	NJ	US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KMC | Draw De

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3. Document ID: US 20030191728 A1

L5: Entry 3 of 10 File: PGPB Oct 9, 2003

PGPUB-DOCUMENT-NUMBER: 20030191728
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20030191728 A1

TITLE: Performance of artificial neural network models in the presence of instrumental noise and measurement errors

PUBLICATION-DATE: October 9, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Kulkarni, Bhaskar Dattatray	Pune		IN	
Tambe, Sanjeev Shrikrishna	Pune		IN	
Lonari, Jayaram Budhaji	Pune		IN	
Valecha, Neelamkumar	Mumbai		IN	
Dheshmukh, Sanjay Vasantrao	Mumbai		IN	
Shenoy, Bhavanishankar	Mumbia		IN	
Ravichandran, Sivaraman	Mumbai		IN	

US-CL-CURRENT: 706/21; 706/31

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KMC | Draw De

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4. Document ID: US 20030140023 A1

L5: Entry 4 of 10 File: PGPB Jul 24, 2003

PGPUB-DOCUMENT-NUMBER: 20030140023
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20030140023 A1

TITLE: System and method for pre-processing input data to a non-linear model for use in electronic commerce

PUBLICATION-DATE: July 24, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Ferguson, Bruce	Round Rock	TX	US	
Hartman, Eric	Austin	TX	US	

US-CL-CURRENT: 706/21; 706/15

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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☐ 5. Document ID: US 20030078901 A1

L5: Entry 5 of 10 File: PGPB Apr 24, 2003

PGPUB-DOCUMENT-NUMBER: 20030078901
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20030078901 A1

TITLE: Neural network based predication and optimization for groundwater / surface water system

PUBLICATION-DATE: April 24, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Coppola, Emery J. JR.	Lawrenceville	NJ	US	
Poulton, Mary M.	Tucson	AZ	US	
Szidarovszky, Ferenc			US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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☐ 6. Document ID: US 20020046199 A1

L5: Entry 6 of 10 File: PGPB Apr 18, 2002

PGPUB-DOCUMENT-NUMBER: 20020046199
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20020046199 A1

TITLE: Electronic employee selection systems and methods

PUBLICATION-DATE: April 18, 2002

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Scarborough, David J.	West Linn	OR	US	
Chambless, Bjorn	Portland	OR	US	
Becker, Richard W.	Portland	OR	US	
Check, Thomas F.	Beaverton	OR	US	
Clainos, Deme M.	Lake Oswego	OR	US	

Eng, Maxwell W.	Portland	OR	US
Levy, Joel R.	Portland	OR	US
Mertz, Adam N.	Portland	OR	US
Paajanen, George E.	West Linn	OR	US
Smith, David R.	Beaverton	OR	US
Smith, John R.	Hillsboro	OR	US

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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☐ 7. Document ID: US 20020042786 A1

L5: Entry 7 of 10 File: PGPB Apr 11, 2002

PGPUB-DOCUMENT-NUMBER: 20020042786
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20020042786 A1

TITLE: Development of electronic employee selection systems and methods

PUBLICATION-DATE: April 11, 2002

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Scarborough, David J.	West Linn	OR	US	
Chambless, Bjorn	Portland	OR	US	
Becker, Richard W.	Portland	OR	US	
Check, Thomas F.	Beaverton	OR	US	
Clainos, Deme M.	Lake Oswego	OR	US	
Eng, Maxwell W.	Portland	OR	US	
Levy, Joel R.	Portland	OR	US	
Mertz, Adam N.	Portland	OR	US	
Paajanen, George E.	West Linn	OR	US	
Smith, David R.	Beaverton	OR	US	
Smith, John R.	Hillsboro	OR	US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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☐ 8. Document ID: US 6879971 B1

L5: Entry 8 of 10 File: USPT Apr 12, 2005

US-PAT-NO: 6879971
DOCUMENT-IDENTIFIER: US 6879971 B1

TITLE: Automated method for building a model

DATE-ISSUED: April 12, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Keeler; James D.	Austin	TX		
Hartman; Eric J.	Austin	TX		
Godbole; Devendra B.	Austin	TX		
Piche; Steve	Austin	TX		
Arbila; Laura	Austin	TX		
Ellinger; Joshua	Austin	TX		
Ferguson, II; R. Bruce	Round Rock	TX		
Krauskop; John	Austin	TX		
Kempf; Jill L.	Austin	TX		
O'Hara; Steven A.	Round Rock	TX		
Strauss; Audrey	Austin	TX		
Telang; Jitendra W.	Austin	TX		

US-CL-CURRENT: 706/21; 706/15, 706/23, 706/903, 706/906, 706/907

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

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9. Document ID: US 6647377 B2

L5: Entry 9 of 10 File: USPT Nov 11, 2003

US-PAT-NO: 6647377
DOCUMENT-IDENTIFIER: US 6647377 B2

TITLE: Multi-kernel neural network concurrent learning, monitoring, and forecasting system

DATE-ISSUED: November 11, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Jannarone; Robert J.	Atlanta	GA		

US-CL-CURRENT: 706/16; 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

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10. Document ID: US 6243696 B1

L5: Entry 10 of 10 File: USPT Jun 5, 2001

US-PAT-NO: 6243696
DOCUMENT-IDENTIFIER: US 6243696 B1

TITLE: Automated method for building a model

DATE-ISSUED: June 5, 2001

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Keeler; James D.	Austin	TX		
Hartman; Eric J.	Austin	TX		
Godbole; Devendra B.	Austin	TX		
Piche; Steve	Austin	TX		
Arbila; Laura	Austin	TX		
Ellinger; Joshua	Austin	TX		
Ferguson, II; R. Bruce	Round Rock	TX		
Krauskop; John	Austin	TX		
Kempf; Jill L.	Austin	TX		
O'Hara; Steven A.	Round Rock	TX		
Strauss; Audrey	Austin	TX		
Telang; Jitendra W.	Austin	TX		

US-CL-CURRENT: 706/21; 706/906, 706/907

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs | Generate OACS

Terms	Documents
L4 and predict$5 and train$5	10

Display Format: - Change Format

Previous Page Next Page Go to Doc#

Refine Search

Search Results -

Terms	Documents
L5 and (wear or deteriorate or fatifue or diminish)	1

Database:

US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search: L6

Refine Search

Recall Text Clear Interrupt

Search History

DATE: Monday, August 01, 2005 Printable Copy Create Case

Set Name side by side	**Query**	**Hit Count**	**Set Name** result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L6	L5 and (wear or deteriorate or fatifue or diminish)	1	L6
L5	L4 and predict$5 and train$5	10	L5
L4	L1 and coefficients and radial near basis and neural	10	L4
L3	monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	3	L3
L2	L1 and monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	0	L2
L1	706/21.ccls.	177	L1

END OF SEARCH HISTORY

Hit List

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs | Generate OACS

Search Results - Record(s) 1 through 1 of 1 returned.

☐ 1. Document ID: US 20040059694 A1

L6: Entry 1 of 1 File: PGPB Mar 25, 2004

PGPUB-DOCUMENT-NUMBER: 20040059694
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20040059694 A1

TITLE: Method and apparatus for providing a virtual age estimation for remaining lifetime prediction of a system using neural networks

PUBLICATION-DATE: March 25, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Darken, Christian J.	Carmel Valley	CA	US	
Loecher, Markus	Princeton Jct.	NJ	US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs | Generate OACS

Terms	Documents
L5 and (wear or deteriorate or fatifue or diminish)	1

Display Format: - Change Format

Previous Page Next Page Go to Doc#

Refine Search

Search Results -

Terms	Documents
(wear or deteriorate or fatifue or diminish) and coefficients and radial near basis and neural near network and predict$5 and train$5	20

Database:

US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search: L7

Refine Search

Recall Text

Clear

Interrupt

Search History

DATE: Monday, August 01, 2005 Printable Copy Create Case

Set Name side by side	**Query**	**Hit Count**	**Set Name** result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L7	(wear or deteriorate or fatifue or diminish) and coefficients and radial near basis and neural near network and predict$5 and train$5	20	L7
L6	L5 and (wear or deteriorate or fatifue or diminish)	1	L6
L5	L4 and predict$5 and train$5	10	L5
L4	L1 and coefficients and radial near basis and neural	10	L4
L3	monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	3	L3
L2	L1 and monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	0	L2
L1	706/21.ccls.	177	L1

END OF SEARCH HISTORY

Hit List

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs | Generate OACS

Search Results - Record(s) 1 through 20 of 20 returned.

☐ 1. Document ID: US 20050165556 A1

L7: Entry 1 of 20 File: PGPB Jul 28, 2005

PGPUB-DOCUMENT-NUMBER: 20050165556
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20050165556 A1

TITLE: Colon cancer biomarkers

PUBLICATION-DATE: July 28, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Barnhill, Stephen	Savannah	GA	US	
Weston, Jason	New York	NY	US	
Guyon, Isabelle	Berkeley	CA	US	

US-CL-CURRENT: 702/19

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KMC | Draw De

☐ 2. Document ID: US 20050096873 A1

L7: Entry 2 of 20 File: PGPB May 5, 2005

PGPUB-DOCUMENT-NUMBER: 20050096873
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20050096873 A1

TITLE: METHOD AND SYSTEM FOR DIAGNOSTICS AND PROGNOSTICS OF A MECHANICAL SYSTEM

PUBLICATION-DATE: May 5, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Klein, Renata	Misgav		IL	

US-CL-CURRENT: 702/184

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KMC | Draw De

☐ 3. Document ID: US 20050075846 A1

L7: Entry 3 of 20 File: PGPB Apr 7, 2005

PGPUB-DOCUMENT-NUMBER: 20050075846
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20050075846 A1

TITLE: Methods for monitoring structural health conditions

PUBLICATION-DATE: April 7, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Kim, Hyeung-Yun	Palo Alto	CA	US	

US-CL-CURRENT: 703/1

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

☐ 4. Document ID: US 20050066075 A1

L7: Entry 4 of 20 File: PGPB Mar 24, 2005

PGPUB-DOCUMENT-NUMBER: 20050066075
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20050066075 A1

TITLE: Method, apparatus and software for lossy data compression and function estimation

PUBLICATION-DATE: March 24, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Kecman, Vojislav	Auckland		NZ	
Robinson, Jonathan	Christchurch		NZ	

US-CL-CURRENT: 710/31

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

☐ 5. Document ID: US 20040206189 A1

L7: Entry 5 of 20 File: PGPB Oct 21, 2004

PGPUB-DOCUMENT-NUMBER: 20040206189
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20040206189 A1

TITLE: Correcting for two-phase flow in a digital flowmeter

PUBLICATION-DATE: October 21, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Henry, Manus P.	Oxford		GB	
De La Fuente, Maria Jesus	Valladolid		ES	

US-CL-CURRENT: 73/861.356

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw. D

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6. Document ID: US 20040059694 A1

L7: Entry 6 of 20 File: PGPB Mar 25, 2004

PGPUB-DOCUMENT-NUMBER: 20040059694
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20040059694 A1

TITLE: Method and apparatus for providing a virtual age estimation for remaining lifetime prediction of a system using neural networks

PUBLICATION-DATE: March 25, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Darken, Christian J.	Carmel Valley	CA	US	
Loecher, Markus	Princeton Jct.	NJ	US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw. De

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7. Document ID: US 20030200189 A1

L7: Entry 7 of 20 File: PGPB Oct 23, 2003

PGPUB-DOCUMENT-NUMBER: 20030200189
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20030200189 A1

TITLE: Automatic neural-net model generation and maintenance

PUBLICATION-DATE: October 23, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Meng, Zhuo	Broadview Heights	OH	US	

Pao, Yoh-Han	Cleveland Heights	OH	US

US-CL-CURRENT: 706/26

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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☐ 8. Document ID: US 20030172043 A1

L7: Entry 8 of 20 File: PGPB Sep 11, 2003

PGPUB-DOCUMENT-NUMBER: 20030172043
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20030172043 A1

TITLE: Methods of identifying patterns in biological systems and uses thereof

PUBLICATION-DATE: September 11, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Guyon, Isabelle	Berkeley	CA	US	
Weston, Jason	St. Leonard's on Sea		GB	

US-CL-CURRENT: 706/48

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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☐ 9. Document ID: US 20030154804 A1

L7: Entry 9 of 20 File: PGPB Aug 21, 2003

PGPUB-DOCUMENT-NUMBER: 20030154804
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20030154804 A1

TITLE: Correcting for two-phase flow in a digital flowmeter

PUBLICATION-DATE: August 21, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Henry, Manus P.	Oxford		GB	
Fuente, Maria Jesus De La	Valladolid		ES	

US-CL-CURRENT: 73/861.356

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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☐ 10. Document ID: US 20010045134 A1

L7: Entry 10 of 20 File: PGPB Nov 29, 2001

PGPUB-DOCUMENT-NUMBER: 20010045134
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20010045134 A1

TITLE: Correcting for two-phase flow in a digital flowmeter

PUBLICATION-DATE: November 29, 2001

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Henry, Manus P.	Oxford		GB	
De La Fuente, Maria Jesus	Valladolid		ES	

US-CL-CURRENT: 73/861.356

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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☐ 11. Document ID: US 6882990 B1

L7: Entry 11 of 20 File: USPT Apr 19, 2005

US-PAT-NO: 6882990
DOCUMENT-IDENTIFIER: US 6882990 B1

TITLE: Methods of identifying biological patterns using multiple data sets

DATE-ISSUED: April 19, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Barnhill; Stephen	Savannah	GA		
Guyon; Isabelle	Berkeley	CA		
Weston; Jason	New York	NY		

US-CL-CURRENT: 706/16; 706/12

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

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☐ 12. Document ID: US 6799141 B1

L7: Entry 12 of 20 File: USPT Sep 28, 2004

US-PAT-NO: 6799141
DOCUMENT-IDENTIFIER: US 6799141 B1

TITLE: Method for determining the channel gain between emitters and receivers

DATE-ISSUED: September 28, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Stoustrup; Jakob	Sk.o slashed.rping			DK
Cour-Harbo; Anders La	Nibe			DK

US-CL-CURRENT: 702/159; 342/192, 342/204, 342/61, 345/158, 345/163

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

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☐ 13. Document ID: US 6789069 B1

L7: Entry 13 of 20 File: USPT Sep 7, 2004

US-PAT-NO: 6789069
DOCUMENT-IDENTIFIER: US 6789069 B1

TITLE: Method for enhancing knowledge discovered from biological data using a learning machine

DATE-ISSUED: September 7, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Barnhill; Stephen	Savannah	GA		
Guyon; Isabelle	Berkeley	CA		
Weston; Jason	New York	NY		

US-CL-CURRENT: 706/12; 706/45

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

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☐ 14. Document ID: US 6760715 B1

L7: Entry 14 of 20 File: USPT Jul 6, 2004

US-PAT-NO: 6760715
DOCUMENT-IDENTIFIER: US 6760715 B1

TITLE: Enhancing biological knowledge discovery using multiples support vector machines

DATE-ISSUED: July 6, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Barnhill; Stephen	Savannah	GA		
Guyon; Isabelle	Berkeley	CA		
Weston; Jason	New York	NY		

US-CL-CURRENT: 706/16; 706/12, 706/20, 706/25, 706/45

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

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15. Document ID: US 6758102 B2

L7: Entry 15 of 20 File: USPT Jul 6, 2004

US-PAT-NO: 6758102
DOCUMENT-IDENTIFIER: US 6758102 B2

TITLE: Correcting for two-phase flow in a digital flowmeter

DATE-ISSUED: July 6, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Henry; Manus P.	Oxford			GB
Fuente; Maria Jesus De La	Valladolid			ES

US-CL-CURRENT: 73/861.356

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

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16. Document ID: US 6714925 B1

L7: Entry 16 of 20 File: USPT Mar 30, 2004

US-PAT-NO: 6714925
DOCUMENT-IDENTIFIER: US 6714925 B1

TITLE: System for identifying patterns in biological data using a distributed network

DATE-ISSUED: March 30, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Barnhill; Stephen	Savannah	GA		
Guyon; Isabelle	Berkeley	CA		
Weston; Jason	New York	NY		

US-CL-CURRENT: 706/48; 706/16

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

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17. Document ID: US 6625569 B2

L7: Entry 17 of 20 File: USPT Sep 23, 2003

US-PAT-NO: 6625569
DOCUMENT-IDENTIFIER: US 6625569 B2

TITLE: Real-time spatio-temporal coherence estimation for autonomous mode identification and invariance tracking

DATE-ISSUED: September 23, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
James; Mark L.	Pasadena	CA		
Mackey; Ryan M. E.	Pasadena	CA		
Park; Han G.	Arcadia	CA		
Zak; Michail	Cypress	CA		

US-CL-CURRENT: 702/183; 702/104, 702/190, 702/191, 702/196, 702/84

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

18. Document ID: US 6581048 B1

L7: Entry 18 of 20 File: USPT Jun 17, 2003

US-PAT-NO: 6581048
DOCUMENT-IDENTIFIER: US 6581048 B1

TITLE: 3-brain architecture for an intelligent decision and control system

DATE-ISSUED: June 17, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Werbos; Paul J.	Arlington	VA	22202	

US-CL-CURRENT: 706/23; 250/369, 706/16

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

19. Document ID: US 6505519 B2

L7: Entry 19 of 20 File: USPT Jan 14, 2003

US-PAT-NO: 6505519
DOCUMENT-IDENTIFIER: US 6505519 B2

TITLE: Correcting for two-phase flow in a digital flowmeter

DATE-ISSUED: January 14, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Henry; Manus P.	Oxford			GB
de la Fuente; Maria Jesus	Valladolid			ES

US-CL-CURRENT: 73/861.356

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

20. Document ID: US 6169981 B1

L7: Entry 20 of 20 File: USPT Jan 2, 2001

US-PAT-NO: 6169981
DOCUMENT-IDENTIFIER: US 6169981 B1

TITLE: 3-brain architecture for an intelligent decision and control system

DATE-ISSUED: January 2, 2001

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Werbos; Paul J.	College Park	MD	20740-2403	

US-CL-CURRENT: 706/23; 706/15, 706/16, 706/26, 706/27

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs | Generate OACS

Terms	Documents
(wear or deteriorate or fatifue or diminish) and coefficients and radial near basis and neural near network and predict$5 and train$5	20

Display Format: - Change Format

Previous Page Next Page Go to Doc#

Refine Search

Search Results -

Terms	Documents
L8 and (formula or algorithm)	19

Database:
US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search: L9

Refine Search

Recall Text Clear Interrupt

Search History

DATE: Monday, August 01, 2005 Printable Copy Create Case

Set Name side by side	**Query**	**Hit Count**	**Set Name** result set
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L9	L8 and (formula or algorithm)	19	L9
L8	L7 and ag$5	20	L8
L7	(wear or deteriorate or fatifue or diminish) and coefficients and radial near basis and neural near network and predict$5 and train$5	20	L7
L6	L5 and (wear or deteriorate or fatifue or diminish)	1	L6
L5	L4 and predict$5 and train$5	10	L5
L4	L1 and coefficients and radial near basis and neural	10	L4
L3	monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	3	L3
L2	L1 and monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	0	L2
L1	706/21.ccls.	177	L1

END OF SEARCH HISTORY

Hit List

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs
Generate OACS

Search Results - Record(s) 1 through 19 of 19 returned.

☐ 1. Document ID: US 20050165556 A1

L9: Entry 1 of 19 File: PGPB Jul 28, 2005

PGPUB-DOCUMENT-NUMBER: 20050165556
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20050165556 A1

TITLE: Colon cancer biomarkers

PUBLICATION-DATE: July 28, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Barnhill, Stephen	Savannah	GA	US	
Weston, Jason	New York	NY	US	
Guyon, Isabelle	Berkeley	CA	US	

US-CL-CURRENT: 702/19

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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☐ 2. Document ID: US 20050096873 A1

L9: Entry 2 of 19 File: PGPB May 5, 2005

PGPUB-DOCUMENT-NUMBER: 20050096873
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20050096873 A1

TITLE: METHOD AND SYSTEM FOR DIAGNOSTICS AND PROGNOSTICS OF A MECHANICAL SYSTEM

PUBLICATION-DATE: May 5, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Klein, Renata	Misgav		IL	

US-CL-CURRENT: 702/184

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

☐ 3. Document ID: US 20050075846 A1

L9: Entry 3 of 19 File: PGPB Apr 7, 2005

PGPUB-DOCUMENT-NUMBER: 20050075846
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20050075846 A1

TITLE: Methods for monitoring structural health conditions

PUBLICATION-DATE: April 7, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Kim, Hyeung-Yun	Palo Alto	CA	US	

US-CL-CURRENT: 703/1

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

☐ 4. Document ID: US 20050066075 A1

L9: Entry 4 of 19 File: PGPB Mar 24, 2005

PGPUB-DOCUMENT-NUMBER: 20050066075
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20050066075 A1

TITLE: Method, apparatus and software for lossy data compression and function estimation

PUBLICATION-DATE: March 24, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Kecman, Vojislav	Auckland		NZ	
Robinson, Jonathan	Christchurch		NZ	

US-CL-CURRENT: 710/31

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

☐ 5. Document ID: US 20040206189 A1

L9: Entry 5 of 19 File: PGPB Oct 21, 2004

PGPUB-DOCUMENT-NUMBER: 20040206189
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20040206189 A1

TITLE: Correcting for two-phase flow in a digital flowmeter

PUBLICATION-DATE: October 21, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Henry, Manus P.	Oxford		GB	
De La Fuente, Maria Jesus	Valladolid		ES	

US-CL-CURRENT: 73/861.356

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw. D

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6. Document ID: US 20040059694 A1

L9: Entry 6 of 19 File: PGPB Mar 25, 2004

PGPUB-DOCUMENT-NUMBER: 20040059694
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20040059694 A1

TITLE: Method and apparatus for providing a virtual age estimation for remaining lifetime prediction of a system using neural networks

PUBLICATION-DATE: March 25, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Darken, Christian J.	Carmel Valley	CA	US	
Loecher, Markus	Princeton Jct.	NJ	US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw. D

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7. Document ID: US 20030172043 A1

L9: Entry 7 of 19 File: PGPB Sep 11, 2003

PGPUB-DOCUMENT-NUMBER: 20030172043
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20030172043 A1

TITLE: Methods of identifying patterns in biological systems and uses thereof

PUBLICATION-DATE: September 11, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Guyon, Isabelle	Berkeley	CA	US	

Weston, Jason St. Leonard's on Sea GB

US-CL-CURRENT: 706/48

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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8. Document ID: US 20030154804 A1

L9: Entry 8 of 19 File: PGPB Aug 21, 2003

PGPUB-DOCUMENT-NUMBER: 20030154804
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20030154804 A1

TITLE: Correcting for two-phase flow in a digital flowmeter

PUBLICATION-DATE: August 21, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Henry, Manus P.	Oxford		GB	
Fuente, Maria Jesus De La	Valladolid		ES	

US-CL-CURRENT: 73/861.356

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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9. Document ID: US 20010045134 A1

L9: Entry 9 of 19 File: PGPB Nov 29, 2001

PGPUB-DOCUMENT-NUMBER: 20010045134
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20010045134 A1

TITLE: Correcting for two-phase flow in a digital flowmeter

PUBLICATION-DATE: November 29, 2001

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Henry, Manus P.	Oxford		GB	
De La Fuente, Maria Jesus	Valladolid		ES	

US-CL-CURRENT: 73/861.356

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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10. Document ID: US 6882990 B1

L9: Entry 10 of 19 File: USPT Apr 19, 2005

US-PAT-NO: 6882990
DOCUMENT-IDENTIFIER: US 6882990 B1

TITLE: Methods of identifying biological patterns using multiple data sets

DATE-ISSUED: April 19, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Barnhill; Stephen	Savannah	GA		
Guyon; Isabelle	Berkeley	CA		
Weston; Jason	New York	NY		

US-CL-CURRENT: 706/16; 706/12

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

---

11. Document ID: US 6799141 B1

L9: Entry 11 of 19 File: USPT Sep 28, 2004

US-PAT-NO: 6799141
DOCUMENT-IDENTIFIER: US 6799141 B1

TITLE: Method for determining the channel gain between emitters and receivers

DATE-ISSUED: September 28, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Stoustrup; Jakob	Sk.o slashed.rping			DK
Cour-Harbo; Anders La	Nibe			DK

US-CL-CURRENT: 702/159; 342/192, 342/204, 342/61, 345/158, 345/163

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

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12. Document ID: US 6789069 B1

L9: Entry 12 of 19 File: USPT Sep 7, 2004

US-PAT-NO: 6789069
DOCUMENT-IDENTIFIER: US 6789069 B1

TITLE: Method for enhancing knowledge discovered from biological data using a learning machine

DATE-ISSUED: September 7, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Barnhill; Stephen	Savannah	GA		
Guyon; Isabelle	Berkeley	CA		
Weston; Jason	New York	NY		

US-CL-CURRENT: 706/12; 706/45

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw. De

☐ 13. Document ID: US 6760715 B1

L9: Entry 13 of 19 File: USPT Jul 6, 2004

US-PAT-NO: 6760715
DOCUMENT-IDENTIFIER: US 6760715 B1

TITLE: Enhancing biological knowledge discovery using multiples support vector machines

DATE-ISSUED: July 6, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Barnhill; Stephen	Savannah	GA		
Guyon; Isabelle	Berkeley	CA		
Weston; Jason	New York	NY		

US-CL-CURRENT: 706/16; 706/12, 706/20, 706/25, 706/45

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw. De

☐ 14. Document ID: US 6758102 B2

L9: Entry 14 of 19 File: USPT Jul 6, 2004

US-PAT-NO: 6758102
DOCUMENT-IDENTIFIER: US 6758102 B2

TITLE: Correcting for two-phase flow in a digital flowmeter

DATE-ISSUED: July 6, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Henry; Manus P.	Oxford			GB
Fuente; Maria Jesus De La	Valladolid			ES

US-CL-CURRENT: 73/861.356

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

15. Document ID: US 6714925 B1

L9: Entry 15 of 19 File: USPT Mar 30, 2004

US-PAT-NO: 6714925
DOCUMENT-IDENTIFIER: US 6714925 B1

TITLE: System for identifying patterns in biological data using a distributed network

DATE-ISSUED: March 30, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Barnhill; Stephen	Savannah	GA		
Guyon; Isabelle	Berkeley	CA		
Weston; Jason	New York	NY		

US-CL-CURRENT: 706/48; 706/16

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

16. Document ID: US 6625569 B2

L9: Entry 16 of 19 File: USPT Sep 23, 2003

US-PAT-NO: 6625569
DOCUMENT-IDENTIFIER: US 6625569 B2

TITLE: Real-time spatio-temporal coherence estimation for autonomous mode identification and invariance tracking

DATE-ISSUED: September 23, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
James; Mark L.	Pasadena	CA		
Mackey; Ryan M. E.	Pasadena	CA		
Park; Han G.	Arcadia	CA		
Zak; Michail	Cypress	CA		

US-CL-CURRENT: 702/183; 702/104, 702/190, 702/191, 702/196, 702/84

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

17. Document ID: US 6581048 B1

L9: Entry 17 of 19 File: USPT Jun 17, 2003

US-PAT-NO: 6581048
DOCUMENT-IDENTIFIER: US 6581048 B1

TITLE: 3-brain architecture for an intelligent decision and control system

DATE-ISSUED: June 17, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Werbos; Paul J.	Arlington	VA	22202	

US-CL-CURRENT: 706/23; 250/369, 706/16

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw. De

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18. Document ID: US 6505519 B2

L9: Entry 18 of 19 File: USPT Jan 14, 2003

US-PAT-NO: 6505519
DOCUMENT-IDENTIFIER: US 6505519 B2

TITLE: Correcting for two-phase flow in a digital flowmeter

DATE-ISSUED: January 14, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Henry; Manus P.	Oxford			GB
de la Fuente; Maria Jesus	Valladolid			ES

US-CL-CURRENT: 73/861.356

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw. De

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19. Document ID: US 6169981 B1

L9: Entry 19 of 19 File: USPT Jan 2, 2001

US-PAT-NO: 6169981
DOCUMENT-IDENTIFIER: US 6169981 B1

TITLE: 3-brain architecture for an intelligent decision and control system

DATE-ISSUED: January 2, 2001

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Werbos; Paul J.	College Park	MD	20740-2403	

US-CL-CURRENT: 706/23; 706/15, 706/16, 706/26, 706/27

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw. De

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs | Generate OACS

Terms	Documents
L8 and (formula or algorithm)	19

Display Format: - Change Format

Previous Page Next Page Go to Doc#

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Search Results -

Terms	Documents
L7 and (age or aging)	10

Database:
US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search: L10

Refine Search

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Search History

DATE: Monday, August 01, 2005 Printable Copy Create Case

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	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L10	L7 and (age or aging)	10	L10
L9	L8 and (formula or algorithm)	19	L9
L8	L7 and ag$5	20	L8
L7	(wear or deteriorate or fatifue or diminish) and coefficients and radial near basis and neural near network and predict$5 and train$5	20	L7
L6	L5 and (wear or deteriorate or fatifue or diminish)	1	L6
L5	L4 and predict$5 and train$5	10	L5
L4	L1 and coefficients and radial near basis and neural	10	L4
L3	monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	3	L3
L2	L1 and monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	0	L2
L1	706/21.ccls.	177	L1

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Search Results - Record(s) 1 through 10 of 10 returned.

☐ 1. Document ID: US 20050165556 A1

L10: Entry 1 of 10 File: PGPB Jul 28, 2005

PGPUB-DOCUMENT-NUMBER: 20050165556
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20050165556 A1

TITLE: Colon cancer biomarkers

PUBLICATION-DATE: July 28, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Barnhill, Stephen	Savannah	GA	US	
Weston, Jason	New York	NY	US	
Guyon, Isabelle	Berkeley	CA	US	

US-CL-CURRENT: 702/19

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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☐ 2. Document ID: US 20050075846 A1

L10: Entry 2 of 10 File: PGPB Apr 7, 2005

PGPUB-DOCUMENT-NUMBER: 20050075846
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20050075846 A1

TITLE: Methods for monitoring structural health conditions

PUBLICATION-DATE: April 7, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Kim, Hyeung-Yun	Palo Alto	CA	US	

US-CL-CURRENT: 703/1

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

3. Document ID: US 20040059694 A1

L10: Entry 3 of 10 File: PGPB Mar 25, 2004

PGPUB-DOCUMENT-NUMBER: 20040059694
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20040059694 A1

TITLE: Method and apparatus for providing a virtual age estimation for remaining lifetime prediction of a system using neural networks

PUBLICATION-DATE: March 25, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Darken, Christian J.	Carmel Valley	CA	US	
Loecher, Markus	Princeton Jct.	NJ	US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

4. Document ID: US 20030172043 A1

L10: Entry 4 of 10 File: PGPB Sep 11, 2003

PGPUB-DOCUMENT-NUMBER: 20030172043
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20030172043 A1

TITLE: Methods of identifying patterns in biological systems and uses thereof

PUBLICATION-DATE: September 11, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Guyon, Isabelle	Berkeley	CA	US	
Weston, Jason	St. Leonard's on Sea		GB	

US-CL-CURRENT: 706/48

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

5. Document ID: US 6882990 B1

L10: Entry 5 of 10 File: USPT Apr 19, 2005

US-PAT-NO: 6882990
DOCUMENT-IDENTIFIER: US 6882990 B1

TITLE: Methods of identifying biological patterns using multiple data sets

DATE-ISSUED: April 19, 2005

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Barnhill; Stephen	Savannah	GA		
Guyon; Isabelle	Berkeley	CA		
Weston; Jason	New York	NY		

US-CL-CURRENT: 706/16; 706/12

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

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6. Document ID: US 6789069 B1

L10: Entry 6 of 10 File: USPT Sep 7, 2004

US-PAT-NO: 6789069
DOCUMENT-IDENTIFIER: US 6789069 B1

TITLE: Method for enhancing knowledge discovered from biological data using a learning machine

DATE-ISSUED: September 7, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Barnhill; Stephen	Savannah	GA		
Guyon; Isabelle	Berkeley	CA		
Weston; Jason	New York	NY		

US-CL-CURRENT: 706/12; 706/45

Full | Title | Citation | Front | Review | Classification | Date | Reference | Claims | KWIC | Draw De

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7. Document ID: US 6760715 B1

L10: Entry 7 of 10 File: USPT Jul 6, 2004

US-PAT-NO: 6760715
DOCUMENT-IDENTIFIER: US 6760715 B1

TITLE: Enhancing biological knowledge discovery using multiples support vector machines

DATE-ISSUED: July 6, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY

Barnhill; Stephen	Savannah	GA
Guyon; Isabelle	Berkeley	CA
Weston; Jason	New York	NY

US-CL-CURRENT: 706/16; 706/12, 706/20, 706/25, 706/45

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

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8. Document ID: US 6714925 B1

L10: Entry 8 of 10 File: USPT Mar 30, 2004

US-PAT-NO: 6714925
DOCUMENT-IDENTIFIER: US 6714925 B1

TITLE: System for identifying patterns in biological data using a distributed network

DATE-ISSUED: March 30, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Barnhill; Stephen	Savannah	GA		
Guyon; Isabelle	Berkeley	CA		
Weston; Jason	New York	NY		

US-CL-CURRENT: 706/48; 706/16

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

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9. Document ID: US 6581048 B1

L10: Entry 9 of 10 File: USPT Jun 17, 2003

US-PAT-NO: 6581048
DOCUMENT-IDENTIFIER: US 6581048 B1

TITLE: 3-brain architecture for an intelligent decision and control system

DATE-ISSUED: June 17, 2003

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Werbos; Paul J.	Arlington	VA	22202	

US-CL-CURRENT: 706/23; 250/369, 706/16

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

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10. Document ID: US 6169981 B1

L10: Entry 10 of 10 File: USPT Jan 2, 2001

US-PAT-NO: 6169981
DOCUMENT-IDENTIFIER: US 6169981 B1

TITLE: 3-brain architecture for an intelligent decision and control system

DATE-ISSUED: January 2, 2001

INVENTOR-INFORMATION:

NAME	CITY	STATE	ZIP CODE	COUNTRY
Werbos; Paul J.	College Park	MD	20740-2403	

US-CL-CURRENT: 706/23; 706/15, 706/16, 706/26, 706/27

Full | Title | Citation | Front | Review | Classification | Date | Reference | | | Claims | KWIC | Draw De

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Terms	Documents
L7 and (age or aging)	10

Display Format: - Change Format

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Search Results -

Terms	Documents
L10 and increments	1

Database:
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Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search: L11

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	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L11	L10 and increments	1	L11
L10	L7 and (age or aging)	10	L10
L9	L8 and (formula or algorithm)	19	L9
L8	L7 and ag$5	20	L8
L7	(wear or deteriorate or fatifue or diminish) and coefficients and radial near basis and neural near network and predict$5 and train$5	20	L7
L6	L5 and (wear or deteriorate or fatifue or diminish)	1	L6
L5	L4 and predict$5 and train$5	10	L5
L4	L1 and coefficients and radial near basis and neural	10	L4
L3	monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	3	L3
L2	L1 and monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	0	L2

L1	706/21.ccls.	177	L1

END OF SEARCH HISTORY

Refine Search

Search Results -

Terms	Documents
wear near (increments or metrics) and coefficients and radial near basis and neural near network and predict$5 and train$5	1

Database:
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US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
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Search: L12

Refine Search

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Search History

DATE: Monday, August 01, 2005 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L12	wear near (increments or metrics) and coefficients and radial near basis and neural near network and predict$5 and train$5	1	L12
L11	L10 and increments	1	L11
L10	L7 and (age or aging)	10	L10
L9	L8 and (formula or algorithm)	19	L9
L8	L7 and ag$5	20	L8
L7	(wear or deteriorate or fatifue or diminish) and coefficients and radial near basis and neural near network and predict$5 and train$5	20	L7
L6	L5 and (wear or deteriorate or fatifue or diminish)	1	L6
L5	L4 and predict$5 and train$5	10	L5
L4	L1 and coefficients and radial near basis and neural	10	L4
L3	monitor$4 and predetermined near (parameters or metric$2) and training	3	L3

	near set$2 and devices and wear$4		
L2	L1 and monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	0	L2
L1	706/21.ccls.	177	L1

END OF SEARCH HISTORY

Refine Search

Search Results -

Terms	Documents
L13 and ((wear or deteriorate or fatifue or diminish) near (increments or metrics))and coefficients and radial near basis and neural near network and predict$5 and train$5	1

Database: US Pre-Grant Publication Full-Text Database
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US OCR Full-Text Database
EPO Abstracts Database
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Search: L14

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Search History

DATE: Monday, August 01, 2005 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L14	L13 and ((wear or deteriorate or fatifue or diminish) near (increments or metrics))and coefficients and radial near basis and neural near network and predict$5 and train$5	1	L14
L13	706/12-60.ccls.	5196	L13
L12	wear near (increments or metrics) and coefficients and radial near basis and neural near network and predict$5 and train$5	1	L12
L11	L10 and increments	1	L11
L10	L7 and (age or aging)	10	L10
L9	L8 and (formula or algorithm)	19	L9
L8	L7 and ag$5	20	L8
L7	(wear or deteriorate or fatifue or diminish) and coefficients and radial near basis and neural near network and predict$5 and train$5	20	L7

L6	L5 and (wear or deteriorate or fatifue or diminish)	1	L6
L5	L4 and predict$5 and train$5	10	L5
L4	L1 and coefficients and radial near basis and neural	10	L4
L3	monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	3	L3
L2	L1 and monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	0	L2
L1	706/21.ccls.	177	L1

END OF SEARCH HISTORY

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Search Results - Record(s) 1 through 1 of 1 returned.

☐ 1. Document ID: US 20040059694 A1

L14: Entry 1 of 1 File: PGPB Mar 25, 2004

PGPUB-DOCUMENT-NUMBER: 20040059694
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20040059694 A1

TITLE: Method and apparatus for providing a virtual age estimation for remaining lifetime prediction of a system using neural networks

PUBLICATION-DATE: March 25, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Darken, Christian J.	Carmel Valley	CA	US	
Loecher, Markus	Princeton Jct.	NJ	US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs | Generate OACS

Terms	Documents
L13 and ((wear or deteriorate or fatifue or diminish) near (increments or metrics))and coefficients and radial near basis and neural near network and predict$5 and train$5	1

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Refine Search

Search Results -

Terms	Documents
((wear or deteriorate or fatigue or diminish) near (increments or metrics)) and coefficients and radial near basis and neural near network and predict$5 and train$5	1

Database:
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US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
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Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search: L16

Refine Search

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Search History

DATE: Monday, August 01, 2005 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
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L16	((wear or deteriorate or fatigue or diminish) near (increments or metrics)) and coefficients and radial near basis and neural near network and predict$5 and train$5	1	L16
L15	L13 and ((wear or deteriorate or fatigue or diminish) near (increments or metrics))and coefficients and radial near basis and neural near network and predict$5 and train$5	1	L15
L14	L13 and ((wear or deteriorate or fatifue or diminish) near (increments or metrics))and coefficients and radial near basis and neural near network and predict$5 and train$5	1	L14
L13	706/12-60.ccls.	5196	L13
L12	wear near (increments or metrics) and coefficients and radial near basis and neural near network and predict$5 and train$5	1	L12
L11	L10 and increments	1	L11

L10	L7 and (age or aging)	10	L10
L9	L8 and (formula or algorithm)	19	L9
L8	L7 and ag$5	20	L8
L7	(wear or deteriorate or fatifue or diminish) and coefficients and radial near basis and neural near network and predict$5 and train$5	20	L7
L6	L5 and (wear or deteriorate or fatifue or diminish)	1	L6
L5	L4 and predict$5 and train$5	10	L5
L4	L1 and coefficients and radial near basis and neural	10	L4
L3	monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	3	L3
L2	L1 and monitor$4 and predetermined near (parameters or metric$2) and training near set$2 and devices and wear$4	0	L2
L1	706/21.ccls.	177	L1

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Search Results - Record(s) 1 through 1 of 1 returned.

☐ 1. Document ID: US 20040059694 A1

L15: Entry 1 of 1 File: PGPB Mar 25, 2004

PGPUB-DOCUMENT-NUMBER: 20040059694
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20040059694 A1

TITLE: Method and apparatus for providing a virtual age estimation for remaining lifetime prediction of a system using neural networks

PUBLICATION-DATE: March 25, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Darken, Christian J.	Carmel Valley	CA	US	
Loecher, Markus	Princeton Jct.	NJ	US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

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Terms	Documents
L13 and ((wear or deteriorate or fatigue or diminish) near (increments or metrics))and coefficients and radial near basis and neural near network and predict$5 and train$5	1

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Search Results - Record(s) 1 through 1 of 1 returned.

☐ 1. Document ID: US 20040059694 A1

L16: Entry 1 of 1 File: PGPB Mar 25, 2004

PGPUB-DOCUMENT-NUMBER: 20040059694
PGPUB-FILING-TYPE: new
DOCUMENT-IDENTIFIER: US 20040059694 A1

TITLE: Method and apparatus for providing a virtual age estimation for remaining lifetime prediction of a system using neural networks

PUBLICATION-DATE: March 25, 2004

INVENTOR-INFORMATION:

NAME	CITY	STATE	COUNTRY	RULE-47
Darken, Christian J.	Carmel Valley	CA	US	
Loecher, Markus	Princeton Jct.	NJ	US	

US-CL-CURRENT: 706/21

Full | Title | Citation | Front | Review | Classification | Date | Reference | Sequences | Attachments | Claims | KWIC | Draw De

Clear | Generate Collection | Print | Fwd Refs | Bkwd Refs | Generate OACS

Terms	Documents
((wear or deteriorate or fatigue or diminish) near (increments or metrics)) and coefficients and radial near basis and neural near network and predict$5 and train$5	1

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Computer References

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(30,000 pages of engineering fundamentals and calculators)

Encyclopedia Britannica

Encyclopedia of Software Engineering

Eric Weisstein's World of Mathematics

(A comprehensive online encyclopedia of mathematics.)

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1. **Neural network and conventional classifiers for fluorescence-guided lase**
Gindi, G.R.; Darken, C.J.; O'Brien, K.M.; Stetz, M.L.; Deckelbaum, L.I.;
Biomedical Engineering, IEEE Transactions on
Volume 38, Issue 3, March 1991 Page(s):246 - 252
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Nunes, C.S.; Mendonca, T.F.; Amorim, P.; Ferreira, D.A.; Antunes, L.M.;
Engineering in Medicine and Biology Society, 2004. EMBC 2004. Conference I Annual International Conference of the
Volume 1, 2004 Page(s):865 - 868 Vol.2
Digital Object Identifier 10.1109/IEMBS.2004.1403295
AbstractPlus | Full Text: PDF(136 KB) IEEE CNF

2. **Assessment of bilharziasis history in outcome prediction of bladder canc basis function neural network**
Ji, W.; Naguib, R.N.G.; Ghoneim, M.;
Information Technology Applications in Biomedicine, 2000. Proceedings. 2000 International Conference on
9-10 Nov. 2000 Page(s):268 - 271
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S33	68	S32 AND S23:S24

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S38       151   S28 OR S31 OR S33:S34 OR S37
S39    838044   PR=2001:2005
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S41       131   IDPAT (sorted in duplicate/non-duplicate order)
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S43        24   S42 AND S1:S7
S44        23   S42 AND (S12:S15 OR S21:S24 OR S8:S9)
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011781090 **Image available**
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XRPX Acc No: N98-157054

Fault diagnosis **method for power source e.g. motor of industrial robot - involves detecting failure in diagnosed** apparatus **based on output of** neural network **which considers** computed **angular velocity and** mechanical **momentum of oscillation of diagnosed** apparatus **as input**

Patent Assignee: NISSAN MOTOR CO LTD (NSMO)
Number of Countries: 001 Number of Patents: 001
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
JP 10049223	A	19980220	JP 96202159	A	19960731	199818	B

Priority Applications (No Type Date): JP 96202159 A 19960731
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
JP 10049223	A		7	G05B-023/02	

Fault diagnosis **method for power source e.g. motor of industrial robot...**

...**involves detecting failure in diagnosed** apparatus **based on output of** neural network **which considers** computed **angular velocity and** mechanical **momentum of oscillation of diagnosed** apparatus **as input**

...Abstract (Basic): The method involves detecting the oscillating component emitted by a diagnosed **apparatus** (3) using a waveform data communication module (11). A **calculation** module (12) **computes** the angular velocity and **mechanical** momentum from the detected oscillating component...

...The **computed** angular velocity and **mechanical** momentum are considered inputs, based on the operation state of the diagnosed **apparatus** , for the back propagation **neural network** (13) which appoints and learns the operation of the diagnosed **apparatus** . A decision module (14) determines the failure state of the diagnosed **apparatus** based on the output of the **neural network** .

...

...ADVANTAGE - Performs diagnosis without using FFT analysis. Abnormal state of diagnosed **apparatus** and diagnosis can be shown quantitatively

...Title Terms: **APPARATUS** ;

41/3,K/62 (Item 62 from file: 350)
DIALOG(R)File 350:Derwent WPIX

012597814 **Image available**
WPI Acc No: 1999-403920/199934
XRPX Acc No: N99-301000

Neural network fault diagnostic **system for commercial and military aircraft**

Patent Assignee: MCDONNELL DOUGLAS CORP (MCDD)
Inventor: BOND W E; URNES J M
Number of Countries: 001 Number of Patents: 001
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
US 5919267	A	19990706	US 97833770	A	19970409	199934	B

Priority Applications (No Type Date): US 97833770 A 19970409
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
US 5919267	A		8	G06F-013/00	

Neural network fault diagnostic **system for commercial and military aircraft**

Abstract (Basic):

... actual performance of every subsystems of host system such as aircraft with modeled performance of **neural network** unit in normal and possible failure modes. A **neural network** processor is programmed to employ comparison voting technique to determine operating condition of host system...

... changing operating condition of the system. An INDEPENDENT CLAIM is also included for operation condition **monitoring method** for host **system** .

...

...In aircraft, heavy **equipments** for e.g. earth moving **equipment** , locomotives, ships, power stations like electric and nuclear power plants, wind turbines, automobiles...

...Operating conditions are **monitored** continuously during operation of aircraft which includes subsystems like actuation components, **engines** , hydraulic system, brake system, flight control system and radar systems to ensure safety and operational...

...The figure shows block diagram of **fault diagnostics** system

41/3,K/68 (Item 68 from file: 350)
DIALOG(R)File 350:Derwent WPIX

011589434 **Image available**
WPI Acc No: 1998-006563/199801
XRAM Acc No: C98-002316
XRPX Acc No: N98-005401
Soldering inspection apparatus **using correlation** neural network - **has** artificial intelligence recognition **unit that** recognises breakdown **capacity and** breakdown **conditions based on established boundary conditions using algorithm of shape** recognition
Patent Assignee: SAMSUNG ELECTRONICS CO LTD (SMSU)
Inventor: KIM J; KIM J H
Number of Countries: 003 Number of Patents: 004
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
JP 9275272	A	19971021	JP 96224189	A	19960826	199801	B
KR 97073259	A	19971107	KR 9610514	A	19960408	199846	
US 6023663	A	20000208	US 97833451	A	19970407	200014	
KR 200215	B1	19990615	KR 9610514	A	19960408	200060	

Priority Applications (No Type Date): KR 9610514 A 19960408
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
JP 9275272	A		16	H05K-003/34	
KR 97073259	A			H05K-003/34	
US 6023663	A			G06F-017/00	
KR 200215	B1			H05K-003/34	

Soldering inspection apparatus **using correlation** neural network - ...

...**has** artificial intelligence recognition **unit that** recognises breakdown **capacity and** breakdown **conditions based on established boundary conditions using algorithm of shape** recognition

...Abstract (Basic): The **apparatus** has a **measurement** unit that extracts three- dimensional video image of a solder part (2) under multi-colour ...

...The boundary conditions of the soldered part are established from the obtained video information. An **artificial intelligence recognition** unit **recognises breakdown** capacity and the **breakdown** condition based on established boundary conditions using an algorithm for shape **recognition** .
...

...Avoids influence due to fluctuation of soldering part position. Suits application to problems of tough **breakdown recognition** . Improves reliability
...Title Terms: **APPARATUS** ;

41/3,K/76 (Item 76 from file: 350)
DIALOG(R)File 350:Derwent WPIX

011033474 **Image available**
WPI Acc No: 1997-011398/199701
XRPX Acc No: N97-009979

Neural network **auto-associator appts for diagnosing faults in electrodynamic** machinery **- includes sensing device for** measuring **set of current values for motor being** monitored **and processing device which compares input and output vectors for providing error metric**

Patent Assignee: SIEMENS CORP RES INC (SIEI)
Inventor: HANSON S J; PETSCHE T
Number of Countries: 001 Number of Patents: 001
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
US 5576632	A	19961119	US 94269466	A	19940630	199701	B

Priority Applications (No Type Date): US 94269466 A 19940630
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
US 5576632	A		10	G06G-007/60	

Neural network **auto-associator appts for diagnosing faults in electrodynamic** machinery - ...

...**includes sensing device for** measuring **set of current values for motor being** monitored **and processing device which compares input and output vectors for providing error metric**

...Abstract (Basic): The appts includes a sensing device for **measuring** a set of current values for a motor being **monitored** . A first signal processing device **derives** frequency spectral components associated with the set of current values. A **neural network** auto-associator receives at least a portion of the frequency spectral components and at least...

...ADVANTAGE - Capable of detecting internal fault which will lead to **mechanical breakdown** .

...Title Terms: **APPARATUS** ;

41/3,K/84 (Item 84 from file: 350)
DIALOG(R)File 350:Derwent WPIX

010403311 **Image available**
WPI Acc No: 1995-304625/199540

Fault diagnosis **appts. for production** machine **- has display unit for displaying ladder circuit sequence to be started based on signals output to** neural network

Patent Assignee: NISSAN MOTOR CO LTD (NSMO)
Number of Countries: 001 Number of Patents: 002
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
JP 7200053	A	19950804	JP 93337852	A	19931228	199540	B
JP 3309533	B2	20020729	JP 93337852	A	19931228	200256	

Priority Applications (No Type Date): JP 93337852 A 19931228
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
JP 7200053	A		5	G05B-023/02	
JP 3309533	B2		5	G05B-019/048	Previous Publ. patent JP 7200053

Fault diagnosis **appts. for production** machine - ...

...**display unit for displaying ladder circuit sequence to be started based on signals output to** neural network

...Abstract (Basic): The diagnosis appts. includes a **neural network** (32) and obtains input signals (x1,x2) and output signals (y1,y2) of a ladder...

...R2) related to an internal coil of the ladder network are also output to the **neural network** , along with another set of signals (K1 - Kn...

...All the above signals are used by the **neural network** to **predict** the next starting of the ladder sequence circuit. This result is displayed on a display circuit (38). Thus, trouble in production **machine** is diagnosed, as per the storage data of the ladder circuit...
...Title Terms: **APPARATUS** ;

41/3,K/85 (Item 85 from file: 350)
DIALOG(R)File 350:Derwent WPIX

010339739 **Image available**
WPI Acc No: 1995-241821/199532
XRPX Acc No: N95-188508
Machine **condition** monitoring **and fault** prediction system **- uses combination of** neural networks **export systems physical models and fuzzy logic to identify developing faults**
Patent Assignee: CATERPILLAR INC (CATE)
Inventor: HUANG H; KNAPP G M; LIN C; LIN S; SPOERRE J K; WANG H
Number of Countries: 003 Number of Patents: 003
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
DE 4447288	A1	19950706	DE 4447288	A	19941230	199532	B
FR 2714750	A1	19950707	FR 9415525	A	19941216	199532	
US 5566092	A	19961015	US 93176482	A	19931230	199647	

Priority Applications (No Type Date): US 93176482 A 19931230
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
DE 4447288	A1		50	G05B-017/02	
US 5566092	A		39	G01B-007/00	
FR 2714750	A1			G06F-019/00	

Machine **condition** monitoring **and fault** prediction system - ...

...**uses combination of** neural networks **export systems physical models and fuzzy logic to identify developing faults**

...Abstract (Basic): The system uses a combination of **neural networks** , expert systems, physical models and fuzzy logic. The processing algorithms are implemented using a transputer...

...system. A typical system has a data acquisition module (410), a diagnosis technology module (420), **machine** model module (430), a data bank (440), user interface (450) and a system control module (460). The **machine** model can cover bearing and gears and provides information for training the **neural network** .
...

...USE/ADVANTAGE - For on line fault detector on **machines** . Provides early warning of fault conditions
...Abstract (Equivalent): A method for diagnosing a physical **machine** or process, the method comprising the steps of...

...1) acquiring a first set of data from the physical **machine** or process ...

...3) detecting abnormal conditions in said autoregressive parameter using an overall root means square (RMS) **measurement** and a covariance statistic of an exponentially weighted moving average (EWMA), wherein if an abnormal...

...a) identifying whether said physical **machine** or process has a fault, including...

...i) determining a hypothesis with the aid of a **fault diagnostic** network, and if said **fault diagnostic** network cannot generate a hypothesis, then...

Title Terms: **MACHINE** ;

41/3,K/87 (Item 87 from file: 350)
DIALOG(R)File 350:Derwent WPIX

010044660 **Image available**
WPI Acc No: 1994-312371/199439
XRPX Acc No: N94-245934

Machine **health** monitoring system **using** neural network - **combines vibration analysis techniques and self organising map** neural networks **to perform** fault **detection and** diagnosis **and tachometer and vibration sensors as input devices from** machinery

Patent Assignee: UNIV BRUNEL (UYBR-N)
Inventor: HARRIS T J
Number of Countries: 001 Number of Patents: 002
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
GB 2277151	A	19941019	GB 937096	A	19930405	199439	B
GB 2277151	B	19970625	GB 937096	A	19930405	199728	

Priority Applications (No Type Date): GB 937096 A 19930405
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
GB 2277151	A		6	G01H-017/00	
GB 2277151	B		1	G01H-017/00	

Machine **health** monitoring system **using** neural network - ...

...**combines vibration analysis techniques and self organising map** neural networks **to perform** fault **detection and** diagnosis **and tachometer and vibration sensors as input devices from** machinery

...Abstract (Basic): The analysis system comprises a database of either component specifications within the **machine** to be **monitored** from which a set of key frequencies can be established by control computer with reference to the **machines** running speed, or a set of previously established key frequencies for the **machine** to be **monitored** . The relative amplitudes of the established key frequencies are used by the self organising map...

...spectrum analysis carried out. Running is also collected. The control computer uses the key frequencies **derived** from the database and the running speed to select parts of the vibration spectrum to...

...vector to the self organising map network. Training data is collected and used while the **machine** is running normally...

...ADVANTAGE - Needs only training examples taken from vibration of **machine** when known to be in good condition...

...Abstract (Equivalent): A **method** of **monitoring** **machine** health comprising the steps of storing in a database initial data concerning vibration **derived** from the component specification of a **machine** , running the **machine** normally for training a self-organising **neural** . **network** in conjunction with the initial data so as to establish normal vibration running criteria, and thereafter **monitoring** the **machine** in operative use by comparison of its vibration running data with the running criteria in the **neural** **network** so as to perform **fault** detection and **diagnosis** .

Title Terms: **MACHINE** ;

41/3,K/90 (Item 90 from file: 350)
DIALOG(R)File 350:Derwent WPIX

009635656 **Image available**
WPI Acc No: 1993-329205/199342
XRPX Acc No: N93-254177
Self-diagnosis and self-repair system for electrophotographic image forming appts. - uses artificial intelligence **, knowledge** engineering **and fuzzy inference to develop inference admitting ambiguity from point of view of maintenance and makes self-diagnosis of** machine **state using inference**
Patent Assignee: MITA IND CO LTD (MTAI)
Inventor: MOTEGI Y; SHIMOMURA Y; TOMIYAMA T; UMEDA Y; YOSHIKAWA H
Number of Countries: 005 Number of Patents: 004
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
EP 565761	A1	19931020	EP 92106557	A	19920415	199342	B
US 5467355	A	19951114	US 92867509	A	19920413	199551	N
			US 94299082	A	19940901		
EP 565761	B1	19970709	EP 92106557	A	19920415	199732	
DE 69220776	E	19970814	DE 620776	A	19920415	199738	
			EP 92106557	A	19920415		

Priority Applications (No Type Date): EP 92106557 A 19920415; US 94299082 A 19940901
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
EP 565761	A1	E	35		
Designated States (Regional): DE FR GB IT					
US 5467355	A		25		Cont of application US 92867509
EP 565761	B1	E	35		
Designated States (Regional): DE FR GB IT					
DE 69220776	E				Based on patent EP 565761

... **uses** artificial intelligence **, knowledge** engineering **and fuzzy inference to develop inference admitting ambiguity from point of view of maintenance and makes self-diagnosis of** machine **state using inference**

...Abstract (Basic): The self-diagnosis and repair **system calculates** the amount of **degradation** relative to the time elapsed after the image forming appts. starts to be used, on the basis of **degradation** data representing the relationship between the time elapsed after the appts. starts to be used, and the amount of **degradation** . The **value** of a **parameter** changed by the amount of **degradation calculated ,** is converted into a fuzzy qualitative **value** using membership functions of the **parameter** , and is replaced with an expression used on qualitative data...

...Data sensed by a series of sensors is converted into a fuzzy qualitative **value** using the membership functions of the **parameter** , and is judged on the basis of the fuzzy qualitative **value** as to whether or not a **fault** exists. **Fault diagnosis** is made using as an initial **value** the **value** of the **parameter** changed by the amount of **degradation** . The result of the diagnosis is output as an expression having ambiguity...

...combining fuzzy theory with qualitative inference. Faults serially occurring can be inferred from changes in **values** of **parameters .**

...Abstract (Equivalent): An image forming **apparatus** provided with a self-diagnosis system comprising: a) objective model storage means (15) for storing data representing the image forming **apparatus** as a combination of a plurality of elements, said data including qualitative data representing behaviours or **attributes** of the respective elements, combinational relationships between the elements and **fault diagnosis** knowledge; b) a plurality of sensor means (1a, 1b, 1c) for sensing quantitative **parameter values** representing the functional state for predetermined elements of said image forming **apparatus** and for outputting **current** state data; c) data conversion (2, 3, 11) means for converting the quantitative **parameter values** sensed by the sensor means (1a, 1b, 1c) into **symbolic values** ; d) fault judgment means (16) for judging whether or not a fault exists; and e) **fault diagnosis** means (14) for diagnosing the state of the image forming **apparatus** on the basis of the qualitative data and the **fault diagnosis** knowledge stored in the objective model storage means (15); characterized in that f) said data conversion means (2, 33, 11) converts the quantitative **parameter** data into fuzzy qualitative (FQ) **values** as said **symbolic values** , the FQ **values** for the respective **parameters calculated** on the basis of the qualitative data and membership functions stored in the objective model storage means (15); g) **degradation** data storage means (12) are provided containing **degradation** data representing a relationship between the time elapsed after the image forming **apparatus** starts to be used and the amount of expected **degradation** of at least one **parameter** of the elements constituting said image forming **apparatus** ; h) **degradation** amount **calculation** means (within 12) for **calculating** the amount of expected **degradation** for said at least one **parameter** at the time elapsed after the image forming **apparatus** starts to be used up to the present time on the basis of the **degradation** data stored in the **degradation** data storage means (12); i) change **calculation** means (within 12) for **computing** a fuzzy qualitative **value** of the at least one **parameter** which is changed by the amount of **degradation calculated** by the **degradation** amount **calculation** means (within 12) on the basis of the qualitative data and the membership functions of the **parameter** stored in the objective model storage means (15); wherein the **fault diagnosis** means (14), in response to a judgement that a fault exists by the fault judgment means (16), diagnosis the state of the image forming **apparatus** on the basis of fuzzy qualitative **values** of the respective **parameters** with **degradation** obtained from said change **calculation** means (12), and outputs the result of the diagnosis as an expression having ambiguity as to whether the **measured parameters** belong to the expected **degradation** condition or not...

...Abstract (Equivalent): An image forming **apparatus** provided with a self-diagnosis system, comprising: objective model storage means for storing data that represent the image forming **apparatus** as a combination of a plurality of elements, qualitative **parameter** data that represent, as **parameters** , **attributes** of respective elements of the plurality of elements and a combinational relationship between the elements, **parameter** membership functions corresponding to the **parameters** , and **fault diagnosis** knowledge; **degradation** data storage means for storing **degradation** data representing an amount of **degradation** undergone by at least one component of the image forming **apparatus** after use of the image forming **apparatus** has started; a plurality of sensor means for sensing a functional state of a predetermined portion of the image forming **apparatus** and outputting state data indicative thereof; **degradation** amount **calculation** means for **calculating** the **degradation** of the at least one component from after the image forming **apparatus** starts to be used to the present

time on the basis of **degradation** data stored in the **degradation** data storage means; change **calculation** means for representing as a fuzzy qualitative **value** , the **value** of a changed **parameter** which has been changed by an amount of **degradation** **calculated** by the **degradation** amount **calculation** means from among qualitative **parameter** data stored in the objective model storage means by using the membership function corresponding to the changed **parameter** ; data conversion means for converting state data outputted by the sensor means into a fuzzy qualitative **value** by applying **parameter** membership functions stored in the objective model storage means; fault judgement means of judging whether or not a fault exists by comparing a fuzzy qualitative **value** from the data conversion means with qualitative **parameter** data stored in the objective model storage means; and **fault** **diagnosis** means for diagnosing the functional state of the image forming **apparatus** on the basis of qualitative **parameter** data and **fault** **diagnosis** knowledge stored in the objective model storage means by utilizing as initial conditions a fuzzy qualitative **value** from the change **calculation** means in response to a judgement that a fault exists by the fault judgement means...

...as an expression which has ambiguity and which indicates the state of the image forming **apparatus** .

(

...Title Terms: **APPARATUS** ;

41/3,K/98 (Item 98 from file: 350)
DIALOG(R)File 350:Derwent WPIX

007303236
WPI Acc No: 1987-300243/198743
XRPX Acc No: N87-224291
Residual fatigue life evaluation method **of** mechanical **parts - determining amount of** fatigue **defect on basis of data of depth of deflective region versus amount of** fatigue **defect**
Patent Assignee: MITSUBISHI JUKOGYO KK (MITO)
Inventor: TAKASHI K; TOURU G
Number of Countries: 006 Number of Patents: 005
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
EP 242425	A	19871028	EP 86107348	A	19860530	198743	B
US 4709383	A	19871124	US 86868744	A	19860530	198749	
CA 1244151	A	19881101				198848	
EP 242425	B1	19920812	EP 86107348	A	19860530	199233	
DE 3686414	G	19920917	DE 3686414	A	19860530	199239	
			EP 86107348	A	19860530		

Priority Applications (No Type Date): JP 8690025 A 19860421
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
EP 242425	A	E	13		
Designated States (Regional): CH DE GB LI					
US 4709383	A		10		
EP 242425	B1	E	13	G01N-023/20	
Designated States (Regional): CH DE GB LI					
DE 3686414	G			G01N-023/20	Based on patent EP 242425

Residual fatigue life evaluation method **of** mechanical **parts** ...

...**determining amount of** fatigue **defect on basis of data of depth of deflective region versus amount of** fatigue **defect**

...Abstract (Basic): The **method** of **evaluating** a **residual fatigue life** of **mechanical** parts comprises the **steps** of grinding a surface layer of a **mechanical** part to be inspected by a minute amount to form an inspection surface. Half-width...

...An amount of **fatigue** defect is determined on the basis of the data of the depth of the defective region versus the amount of **fatigue** defect which were separately obtained from a test piece; as well as on the basis...
...ADVANTAGE - Has high precision even in second period of **fatigue** life ...
...Abstract (Equivalent): A **method** for **evaluating** a **residual fatigue life** of **mechanical** parts characterised by the **steps** of: grinding off a surface layer of said **mechanical** part in an area that is to be exposed to X-rays, that has not been exposed to stress and thus can be employed as representing unused material; **measuring** an X-ray intensity curve vs. the angle of diffraction for different positions (X) of said surface; plotting the half-width **value** (H) of said curve against the corresponding **measuring** position (X), where in the plotted function has a linearly **increasing** part followed by a constant horizontal half-width **value** (Ho) which represents the half-width (Hwo) of the unused material; transforming the **measuring**

position (X) to a function of depth (d) of penetration according to the following **equation** : d = R - square root of R squared + (l over 2 minus x)squared - (l over 2)squared. wherein the respective **measuring** position is represented in term of the horizontal coordinate x, the radius of a circular...

...length of the chord formed as an inspection surface is represented by l; deforming a **normalised** half-width function (H/Hwo) versus the depth d; and determining the point do, where the linearly **increasing** part of the function meets the constant part of the intensity curve, which point (do) represents an indication of the **fatigue** defect (delta). (Dwg.1/8)i

...Abstract (Equivalent): A **method** **evaluating** a **residual** **fatigue** **life** of **mechanical** parts consist of the **steps** of grinding a surface layer of a **mechanical** part to be inspected by a minute amount to form an inspection surface, **measuring** half-width data of an X-ray diffraction intensity curve on the inspection surface, **calculating** a depth (do) of a **fatigue** **damaged** region from a graph of a half-width ratio (H/Ho) versus a depth (d) below the surface layer, and determining a fraction of **fatigue** lift N/Nf on the basis of data of the depth (do) of the defective region versus the fraction of **fatigue** life N/Nf which were separately obtained from a test piece. (10pp)o

...Title Terms: **FATIGUE** ;

41/3,K/101 (Item 101 from file: 350)
DIALOG(R)File 350:Derwent WPIX

004212893
WPI Acc No: 1985-039773/198507
XRPX Acc No: N85-029577

Continuous monitoring **of** remaining life **of** machine tool **- using centralised data processor storing depth of cut of each** tool **for comparison of cumulative total with expected useful life**

Patent Assignee: TOYODA KOKI KK (TOZK)
Inventor: OHTA T; SAKAKIBARA Y; YAMAKAGE T
Number of Countries: 002 Number of Patents: 002
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
FR 2548070	A	19850104	FR 8410279	A	19840628	198507	B
US 4628458	A	19861209	US 84621233	A	19840615	198652	

Priority Applications (No Type Date): JP 83118493 A 19830630
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
FR 2548070	A		19		

Continuous monitoring **of** remaining life **of** machine tool - ...
...**using centralised data processor storing depth of cut of each** tool **for comparison of cumulative total with expected useful life**

...Abstract (Basic): The **tool** life **measurement system** uses a control program to permit **monitoring** of multiple **tools** in a manufacturing installation. For each execution of a **numerical** control program the **tool** selection code is detected and the **tool** number memorised. The **machining** depth added to a cumulative total...

...The cumulative **machining** depth is compared, for each **tool** , against a predetermined figure representing the useful life of the **average tool** . The difference between the cumulative total and the expected life can be displayed to indicate whether a **tool** can be expected to last through a further production run...

...ADVANTAGE - Continuous **monitoring** of **tool wear** at a central point to indicate **remaining tool life** .

...Abstract (Equivalent): The detection method comprises the **step** of detecting a **tool** selection code at each execution **step** of the NC program and storing a **tool** number of a **tool currently** in use as **derived** from the **tool** selection code. An **actual machining** distance is **calculated** for the **currently** in use **tool** during **machining** of the workpiece by the **currently** in use **tool** . The **actual machining** distance is accumulated for each **tool** by storing the **actual machining** distance determined in the **calculating step** for each **tool** and by adding to it the **actual machining** distance **calculated** of the respective **tool** .

...

...The accumulated **actual machining** distance is compared with a predetermined **machining** life distance to indicate the lift of each **tool** and the life of each **tool** is determined based on a result obtained in the comparing **step** .

...

...USE/ADVANTAGE - Computerised **numerical** controller. Decides life of each **tool** more accurately. (11pp)
...Title Terms: **MONITOR** ;

47/3,K/6 (Item 6 from file: 350)
DIALOG(R)File 350:Derwent WPIX

014977977 **Image available**
WPI Acc No: 2003-038491/200303
XRPX Acc No: N03-029914

Orthogonal basis function **selection method in** neural network , **involves determining orthogonal** basis function **from orthogonal combination of regressor matrix**

Patent Assignee: US SEC OF AIR FORCE (USAF)
Inventor: CAO Y; CHEN C P; LECLAIR S R
Number of Countries: 001 Number of Patents: 001
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
US 6463341	B1	20021008	US 9887965	A	19980604	200303	B
			US 99326441	A	19990604		

Priority Applications (No Type Date): US 9887965 P 19980604; US 99326441 A 19990604
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
US 6463341	B1		28	G05B-013/02	Provisional application US 9887965

Orthogonal basis function **selection method in** neural network , **involves determining orthogonal** basis function **from orthogonal combination of regressor matrix**

Abstract (Basic):
... A set of orthogonal **basis function** is randomly selected from empirical data and a heterogeneous regressor matrix F' is constructed. The regressor matrix is rearranged to form an orthogonal basis matrix H'. The orthogonal **basis function** hk' of the matrix H' that closely approximates the **actual** function used for creating empirical data in **neural network** , is determined.
... For selecting orthogonal **basis function** set in **neural network** .
...

...Avoids discarding of useful information in **neural network** , by determining the orthogonal **basis function** from the combination of regressor set

47/3,K/17 (Item 17 from file: 350)
DIALOG(R)File 350:Derwent WPIX

012687602 **Image available**
WPI Acc No: 1999-493711/199941
XRPX Acc No: N99-367796
Feedback linearization method of neural networks
Patent Assignee: UNIV TEXAS SYSTEM (TEXA)
Inventor: LEWIS F L; YESILDIREK A
Number of Countries: 001 Number of Patents: 001
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
US 5943660	A	19990824	US 95496493	A	19950628	199941	B
			US 97950581	A	19971015		

Priority Applications (No Type Date): US 95496493 A 19950628; US 97950581 A 19971015
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
US 5943660	A		17	G06F-015/18	Cont of application US 95496493

Feedback linearization method of neural networks

Abstract (Basic):
... is output by comparing sensed state with desired state in initial feedback loop. Unknown function **estimates** are **calculated** as function of sensed state using multilayer **neural network** process having neurons with tunable weights in respective feedback loops. Based on the **estimates** , **smooth** control action is **calculated** and applied to maintain desired **measurable** state.
... In **neural network** and in **neural network** applications such as classification, pattern **recognition** , combinational **optimization** , **system** identification, **prediction** , etc...

...Multilayer **neural networks** offer more than a single layer **neural network** and thus permits application to a much longer class of control systems and also avoids same limitations such as **basis function** set or choosing same centers and variations of **radial basis** type activation functions...

...The figure shows **neural network** controller incorporating feedback linearization...

47/3,K/28 (Item 28 from file: 347)
DIALOG(R)File 347:JAPIO

05630212 **Image available**
LEARNING CONTROL METHOD

PUB. NO.: 09-245012 [JP 9245012 A]
PUBLISHED: September 19, 1997 (19970919)
INVENTOR(s): YAMADA SATOSHI
APPLICANT(s): MITSUBISHI ELECTRIC CORP [000601] (A Japanese Company or Corporation), JP (Japan)
APPL. NO.: 08-052161 [JP 9652161]
FILED: March 08, 1996 (19960308)

...JAPIO CLASS: Computer Applications); 22.3 (**MACHINERY** --

ABSTRACT

... system for which it is required to consider a history in the past by using **evaluation** for the control of the controlled **system** .

...

...SOLUTION: The **measured** result of the state of the controlled **system** 1 is inputted to control systems 2 and 11 formed by **neural networks** provided with internal state storage layers 10 and 15 and provided with neurons for which a **radial basis function** (**RBF** function) is an input/output function as hidden layers 6 and 14 and the **evaluation** for the control of the controlled **system** is judged from the **measured** result of the state of the controlled **system** controlled based on an obtained control output value. Learning is performed by changing the synapse coupling strength of the **neural** network based on the judged result and the controlled system is controlled while repeating the above

Set	Items	Description
S1	931602	PREDICT? OR INTUIT?? OR INTUITING OR FORECAST? OR PROGNOS? OR ANTICIPAT? OR EVALUAT? OR MONITOR? OR MEASUR?
S2	954738	APPROXIMATING OR CALCULAT? OR COMPUTING OR COMPUTE OR COMP-UTES OR COMPUTED OR ESTIMAT? OR APPRAIS? OR ASSESS? OR TREND?-(3N)ANALY? OR INTERPOLAT? OR RECOGNI? OR EXTRAPOLAT? OR DERIV?
S3	566205	S1:S2(7N)(METHOD? OR SYSTEM? OR PROCESS?? OR PROCEDUR? OR -TECHNIQUE? OR MODE?)
S4	105260	(REMAINING? OR REMAINDER? OR AVAILAB? OR LEFT OR RESIDUAL?-)(5N)(LIFE? OR YEAR? OR TIME? OR DAY OR DAYS OR HOUR? OR WEEK? OR MONTH?)
S5	110423	TIME(2W)FAILURE? OR FAULT?(2W)DIAGNOS? OR TIME(2W)OPERATIO-N? OR (WORK? OR OPERATION?)(2N)LIFE? OR BREAKDOWN? OR (BREAK? OR BROKE?)()DOWN
S6	119	(VIRTUAL? OR THEORETIC?)(2N)(AGE OR AGES OR AGING)
S7	1439272	MACHIN? OR EQUIPMENT? OR APPLIANC? OR APPARATUS? OR TOOL? ? OR ENGINE? OR INDUSTR?()DEVICE? OR MECHANIC? OR MECHANISM?
S8	443883	WEAR? OR DAMAG? OR ATTRIT? OR EROSI? OR ERODE? OR ERODING -OR ABRAD? OR DEGENERAT? OR DECLIN? OR WORSEN?
S9	540937	DELAPIDAT? OR EXHAUST? OR FATIGU? OR DEGRAD? OR DETERIORAT? OR ABRAS? OR DECAY? OR DIMINISH?
S10	1209204	PARAMETER? OR VARIABL? OR VALUE? OR QUALITY? OR QUALITIE? -OR CHARACTERISTIC?
S11	851256	ATTRIBUT? OR TRAIT? OR PATTERN? OR COEFFICIENT? OR BEHAVIO-R? OR BEHAVIOUR?
S12	1550598	INCREMENT? OR STEP OR STEPS OR STEPPED OR STEPPING OR AUGM-ENTAT? OR INCREAS? OR UPTICK? OR UP()TICK? OR ADDITION? OR AD-VANC? OR PROGRESSION? OR PROGRESSING? OR STEP(2W)STEP OR STEP-WISE? OR BIT(2W)BIT OR INCH(2W)INCH OR PIECEMEAL?
S13	248716	DECREMENT? OR PROTOCOL? OR GRADATION? OR GRADUAT? OR CUMUL-ATIV?
S14	1507139	SAMPLE? OR TRAINING? OR REPRESENTATIV? OR ILLUSTRATIV? OR -SPECIMEN? OR SYMBOLIC? OR (TEST OR CONTROL? OR REFERENCE?)()(-CASE? OR SET? OR DEVIC?) OR PREDETERMIN? OR OBJECTIVE? OR IDE-AL? OR SIMULAT? OR DESIRED?
S15	1469507	GIVEN? OR ACTUAL? OR EXAMPL? OR LITERAL? OR EXTANT? OR CUR-RENT? OR INSTANT()(CASE? OR DEVIC?) OR REAL OR EXTANT? OR EXI-STING? OR GENUIN? OR DEFACTO? OR DE()FACTO? OR FACTUAL?
S16	72983	NEURAL()NETWORK? OR MACHINE()(LEARN? OR INTELLIGEN?) OR AR-TIFICIAL()INTELLIGEN? OR AI OR GAUSS?()(DISTRIBUT? OR CURVE?) OR FUZZY()(LOGIC? OR INFERENC? OR THEOR?)
S17	2214	RADIAL()BASIS OR BASIS()FUNCTION? OR RBF OR RADIALBASIS? OR BASISFUNCTION? OR RBFN
S18	2	COVER?(2N)THEOREM?(5N)SEPARAB?(5N)PATTERN?
S19	1	(INPUT?(10N)OUTPUT?)(10N)(MAP OR MAPS)(10N)(APPROXIMATOR? -OR APPROXIMATER?)
S20	8	(APPROXIMATOR? OR APPROXIMATER?)(10N)LINEAR?(3N)(COMBINE? -OR COMBINING? OR COMBINATION?)
S21	568772	FORMULA? OR METRIC? OR NUMERICAL? OR ARITHMET? OR MATHEMAT-IC? OR LOGORITHM? OR LOGARITHM?
S22	282974	ALGEBRA? OR EQUATION? OR CALCULUS? OR COMPUTATION? OR ALGO-RITHM? OR ALGARITHM? OR THEOREM?
S23	270	IC=G06E?
S24	2810	S1:S3(10N)S4:S6(10N)S7
S25	329	S24 AND S16
S26	25	S25 AND S17:S20
S27	131	S25 AND S8:S9(10N)S12:S13
S28	313	S25 AND (S12:S13 OR S21:S22)(10N)S8:S11
S29	328	S25 AND S14:S15 AND S8:S11
S30	0	(S25 OR S28 OR S29) AND S23
S31	14	S6 AND S16:S20

```
S32        309   S29 AND S14:S15(10N)S7
S33        329   S25 OR S28:S29 OR S32
S34        145   S33 AND (S1:S3 OR S4:S6 OR S7)/TI
S35          4   S33 AND S16:S20/TI
S36        158   S26 OR S27 OR S31
S37        247   S34:S36
S38        247   IDPAT (sorted in duplicate/non-duplicate order)
S39        130   S38 NOT AD=2001:2005
File 348:EUROPEAN PATENTS 1978-2005/Jul W04
         (c) 2005 European Patent Office
File 349:PCT FULLTEXT 1979-2005/UB=20050728,UT=20050721
         (c) 2005 WIPO/Univentio
?
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39/3,K/42 (Item 42 from file: 348)
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METHOD AND APPARATUS FOR PREPROCESSING INPUT DATA TO A NEURAL NETWORK
VERFAHREN UND ANLAGE ZUR EINGANGSDATENVORVERARBEITUNG FUR EIN NEURONALES NETZWERK
PROCEDE ET APPAREIL DE PRETRAITEMENT DES DONNEES INTRODUITES DANS UN RESEAU NEURONAL
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Available Text	Language	Update	Word Count
CLAIMS B	(English)	200125	1333
CLAIMS B	(German)	200125	1222
CLAIMS B	(French)	200125	1509
SPEC B	(English)	200125	10180
Total word count - document A			0
Total word count - document B			14244
Total word count - documents A + B			14244

...SPECIFICATION Swiss-cheese" data table described above occurs quite often in real-world problems.

Conventional neural **network** **training** and testing methods require complete **patterns** such that they are required to discard **patterns** with missing or bad data. The deletion of the bad data in this manner is an inefficient method for **training** a **neural** **network** . For **example** , suppose that a **neural** **network** has ten inputs and ten outputs, and also suppose that one of the inputs or outputs happens to be missing at the **desired** time for fifty percent or more of the **training** **patterns** . Conventional methods would discard these **patterns** , leading to **training** for those **patterns** during the **train**ing mode and no reliable predicted output during the run mode. This is inefficient, considering that for this case more than ninety percent of the information is still there for the **patterns** that conventional methods would discard. The predicted output corresponding to those certain areas will be...

...the overall data after screening bad or missing data. Additionally, experimental results have shown that **neural network** testing performance generally increases with more **training** data, such that throwing away bad or incomplete data decreases the overall performance of the **neural network** .

In addition to the above, when data is retrieved on different time scales, it is...

...the data on a common time scale. However, this is difficult in that for a **given** time scale, another and longer time scale results in missing data at that position. For **example** , if one set of data were taken on an hourly basis and another set of...

...all data is presented at synchronized times to the system model. Worse yet, the data **sample** periods may be non-periodic, producing totally asynchronous data.

In addition, this data may be...

...be able to read all of these different data formats, keeping track of the data **value** and the time-stamp of the data out to one or more "flat files" which are column oriented, each column corresponding to a data **variable** and/or the data/time stamp of the **variable** . It is a formidable task to retrieve this data keeping track of the date-time...

...aspect of data integrity is that with respect to inherent delays in a system. For **example** , in a chemical processing system, a flow meter output can provide data at time t0)) at a **given** **value** . However, a **given** change in flow resulting in a different reading on the flow meter may not affect the output for a **predetermined** delay (tau). In order to predict what the output would be, this flow meter output...

...network at a delay equal to (tau). This must also be accounted for in the **training** of the network. In generating data that accounts for time delays, it has been postulated...

...original data, wherein only the delayed data is utilized.

Further, in order to change the **value** of the delay, an entirely new set of input data must be generated off the...time merge processor is provided. The pre-time merge processor is operable to apply a **predetermined** algorithm to the input data prior to input to the time merge device. A post...

...part of the output device. The post-time merge processor is operable to apply a **predetermined** algorithm to the data reconciled by the time merge device prior to output as the reconciled data. The **predetermined** algorithms are externally input and stored in a preprocessor memory such that the sequence in which the **predetermined** algorithms were applied is also stored.

In another embodiment of the present invention, the system model utilizes a non-linear network having a set of model **parameters** associated therewith that define the representation of the network, the model **parameters** operable to be trained on a set of **training** data that is received from a run-time system such that the system model is...

...the output of the system and the set of measured input data representing the system **variables** . The target data and system **variables** are

reconciled by the preprocessor and then input to the network. A **training** device is operable to train the non-linear network according to a **predetermined training algorithm** , such that the **values** of the model **parameters** are changed until the network comprises a stored representation of the run-time system.
In...

...of the present invention, the input data is comprised of a plurality of system input **variables** , each of the system input **variables** comprising an associated set of data. A delay device is provided that is operable to provide at least select ones of the input **variables** after preprocessing by the preprocessor and introducing a **predetermined** amount of delay therein to output a delayed input **variable** . This delayed input **variable** is input to the system model. Further, this **predetermined** delay is determined external to the delay device.

BRIEF DESCRIPTION OF THE DRAWINGS
For a...

...1 illustrates an overall block diagram of the system for both preprocessing data during the **training** mode and for preprocessing data during the run mode;
FIGURE 1a illustrates a simplified block...

...of FIGURE 1;
FIGURE 2 illustrates a detailed block diagram of the preprocessor in the **training** mode;
FIGURE 3 illustrates a simplified block diagram of the time merging operation, which is...

...a block diagram of a plan depicting the various places in the process flow that **parameters** occur relative to the plant output;
FIGURE 10 illustrates a diagrammatic view of the relationship between the various plant **parameters** and the plant output;
FIGURE 11 illustrates a diagrammatic view of the delay provided for input data **patterns** ;
FIGURE 12 illustrates a diagrammatic view of the buffer formation for each of the network...

...the display for selection of the delays associated with various inputs and outputs in the **neural network** model;
FIGURE 14 illustrates a block diagram for a **variable** delay selection;
FIGURE 15a illustrates a block diagram of the adaptive determination of the delay;
FIGURE 15b illustrates **examples** of the time-delay functions used in adaptive or **variable** time-delay modes;
FIGURE 16 illustrates a diagrammatic view of a conventional multi-layer **neural network** ;
FIGURE 17 illustrates a flowchart depicting the time delay operation;
FIGURE 18 illustrates a flowchart depicting the run mode operation;
FIGURE 19 illustrates a flowchart for setting the **value** of the **variable** delay; and
FIGURE 20 illustrates a block diagram of the interface of the run time
...

...there is illustrated an overall block diagram of the data preprocessing

operation in both the **training** mode and the run time mode. In the **training** mode, one of more data files 10 are provided, which data files include both input **training** data and output **training** data. The **training** data is arranged in "sets", which sets correspond to different plant **variables** , and which may be **sampled** at different time intervals. This data is referred to as the "raw" data. When the...

...done in such a manner as to keep track of the time stamp for each **variable** . Thus, the "raw" data is organized as time, **value** pairs of columns; that is, for each **variable** xi)), there is its associated time of **sample** ti)). The data can then be grouped into sets (xi)), ti))).

If any of the...

...data will be grouped in common time scale groups, and data that is on, for **example** , a fifteen minute **sample** time scale will be grouped together and data **sampled** on a one hour **sample** time scale will be grouped together. However, any type of format that provides viewing of... hereinbelow. During operation, the preprocessor 12 is operable to store various preprocessing algorithms in a **given** sequence in a storage area 14. As will be described hereinbelow, the sequence defines the...

...data. This operation can be performed on both the target output data and the input **training** data. The delay settings are stored in a storage area 18 after determination thereof.

The output of the delay block 16 is input to a **training** model 20. The **training** model 20 is a non-linear model that receives input data and compares it with...

...for predicting the target output data from the input data. In the preferred embodiment, the **training** model utilizes a multi-layered **neural network** that is trained on one of multiple methods, one being Back Propagation. Various weights within the network are set during the Back Propagation **training** operation, and these are stored as model **parameters** in a storage area 22. The **training** operation and the **neural network** are conventional systems.

A Distributed Control System (DCS) 24 is provided that is operable to generate various system measurements and **control settings** representing system **variables** such as temperature, flow rates, etc., that comprise the input data to a system model...

...inputs to the DCS 24. The run time system model 26 is utilizing the model **parameters** stored in the storage area 22. It should be noted that the run time system model 26 contains a representation learned during the **training** operation, which representation was learned on the preprocessed data. Therefore, data generated by the DCS...

...sequence of preprocessing algorithms stored in the storage area 14, which were generated during the **training** operation. The output of the run time preprocessor 34 is input to a run time...

...the preprocessor 34', the delay 36' and the system model 26' operate in both a **training** mode and a run-time mode. A multiplexer 35 is provided that receives the output...

...the data file(s) 10 and the output of the DCS 24, this providing plant **variables** of the DCS 24, the output of the multiplexer input to the preprocessor 34'. A **control device** 37 is provided that controls the multiplexer 35 to select either a **training** mode or a run-time mode. In

the **training** mode, the data file(s) 10 has the output thereof selected by a multiplexer and the preprocessor 34' is operable to preprocess the data in accordance with a **training** mode, i.e., the preprocessor 34' is utilized to determine what the **predetermined** algorithm sequence is that is stored in the storage area 14. An input/output device I/O 41 is provided for allowing the operator to interface with the **control device** 37. The delay 36' is also controlled by the **control device** 37 to determine the delay settings for storage in the storage area 18. The system model 26' is operated in a **training** mode such that the target data and the input data to the system model 26' are generated, the **training** controlled by **training** block 39. The **training** block 39 is operable to select one of multiple **training** algorithms, such as back propagation, for **training** of the system model 26'. The model **parameters** are stored in the storage area 22.

After **training** , the **control device** 37 places the system in a run-time mode such that the preprocessor 34' is...

...there is illustrated a more detailed block diagram of the preprocessor 12 utilized during the **training** mode. In general, there are three stages to the preprocessing operation. The central operation is...is operable to store the sequence of the various processes that are determined during the **training** mode, these interfaced with a bi-directional bus 60. During the **training** mode, the controller 46 determines which of the functional algorithms are to be applied to...

...seen that the waveform associated with x1))(t) has only a certain number, n, of **sample** points associated therewith. The time-merge operation is a transform that takes one or more columns of data, xi))(ti))), such as that shown in FIGURE 4a, with ni)) time **samples** at times ti))'. That is, the time-merge operation is a function, (OMEGA), that produces a new set of data (x') on a new time sale t' from the **given** set of data x(t) **sampled** at t. This function is done via a variety of conventional extrapolation, interpolation, or box...

...as a C-language callable function as: where xi)), ti)) are vectors of the old **values** and old times; xi))'... xk))' are vectors of the new **values** ; and t' is the new time-scale vector.

Referring now to FIGURE 5a, there is...

...The data table consists of data with time disposed along a vertical scale and the **samples** disposed along a horizontal scale. Each **sample** comprises many different pieces of data with two data intervals illustrated. It can be seen that when the data is examined for both the data **sampled** at the time interval "1" and the data **sampled** at the time interval "2", that some portions of the data result in incomplete **patterns** . This is illustrated by a dotted line 63, where it can be seen that some data is missing in the data **sampled** at time interval "1" and some is missing in time interval "2". A complete **neural network pattern** is illustrated box 64, where all the data is complete. Of interest is the time difference between the data **sampled** at time interval "1" and the data **sampled** at time interval "2". In time interval "1", the data is essentially present for all steps in time, whereas data **sampled** at time interval "2" is only **sampled** periodically relative to data **sampled** at time interval "1". As such, a data reconciliation procedure is implemented that fills in the missing data and also reconciles between the time **samples** in time interval "2" such that the data is complete for all time **samples** for both time

interval "1" and time interval "2".

The **neural network** models that are utilized for time-series prediction and control require that the time-interval between successive **training patterns** be constant. Since the data that comes in from **real** -world systems is not always on the same time scale, it is desirable to time-merge the data before it can be used for **training** or running the **neural network** model. To achieve this time-merge operation, it may be necessary to extrapolate, interpolate, average...

...the data in each column over each time-region so as to give an input **value** x'(t) that is on the appropriate time-scale. All of these are referred to...

...algorithm utilized may include linear estimates, spline-fit, boxcar algorithms, etc. If the data is **sampled** too frequently in the time-interval, it will be necessary to smooth or average the data to get a **sample** on the **desired** time scale. This can be done by window averaging techniques, sparse- **sample** techniques or spline techniques.

In general, x'(t) is a function of all of the raw **values** x(t) **given** at present and past times up to some maximum past time, Xmax. That is, where some of the **values** of xi))(tj))) may be missing or bad.

This method of finding x'(t) using past **values** is strictly extrapolation. Since the system only has past **values** available during runtime mode, the **values** must be reconciled. The simplest method of doing this is to take the next extrapolated **value** x'i))(t) = xi))(tN))); that is, take the last **value** that was reported. More elaborate extrapolation **algorithms** may use past **values** xi))(t-(tau)ij))), j(set membership)t(o, ... imax))). For **example** , linear extrapolation would use: Polynomial, spline-fit or **neural** - **network** extrapolation techniques use Equation 3. (See eg. W.H. Press, "Numerical Recipes", Cambridge University Press (1986), pp. 77-101) **Training** of the neural net would **actually** use interpolated **values** , i.e., **Equation** 4, wherein the case of interpolation tN))>t.

Referring now to FIGURE 5b, there is illustrated an input data **pattern** and target output data **pattern** illustrating the pre-process operation for both preprocessing input data to provide time merged output...

...and also preprocessing the target output data to provide pre-processed target output data for **training** purposes. The data input x(t) is comprised of a vector with many inputs, x1...

...or interpolated to insure that all data is present on a single time scale. For **example** , if the data at x1))(t) were on a time scale of one **sample** every second, a **sample** represented by the time tk)), and the output time scale were **desired** to be the same, this would require time merging the rest of the data to...

...it is illustrated as being synchronized. The data buffer in FIGURE 4b is illustrated in **actual** time. The reconciliation could be as simple as holding the last **value** of the input x2))(t) until a new **value** is input thereto, and then discarding the old **value** . In this manner, an output will always exist. This would also be the case for...

...on one time scale and the data x2))(t) is on a different time scale **Additionally** , one **value** of the data set x1))(t) is illustrated as being bad, which piece of bad...

...the preprocessing mode fills in this bad data and then time merges it.

In this **example** , the time scale for x1))(t) is utilized as a time scale for the time...

...the time merge data x1))'(t) is on the same time scale with the "cut" **value** filled in as a result of the preprocessing operation and the data set x2))(t...

...manually preprocess the data. In manual preprocessing of data, the data is viewed in a **desired** format by the operator and the operator can look at the data and eliminate, "cut" or otherwise modify obviously bad data **values** . This is to be compared to the automatic operation wherein all **values** are subjected to a **predetermined** **algorithm** to process the data. For **example** , if the operator noticed that one data **value** is significantly out of range with the normal **behavior** of the remaining data, this data **value** can be "cut" such that it is no longer present in the data set and...

...However, an algorithm could be generated that either cuts out all data above a certain **value** or clips the **values** to a **predetermined** maximum. The clipping to a **predetermined** maximum is an algorithmic operation that is described hereinbelow.

After displaying and processing the data...

...Y" block to a function block 80 to select a particular algorithmic process for a **given** set of data. After selecting the algorithmic process, the program flows to a function block...

...function block 80 along a "Y" path. Once all data has been subjected to the **desired** algorithmic processes, the program flows along a "N" path from decision block 84 to a...

...86 to store the sequence of algorithmic processes such that each data set has the **desired** algorithmic processes applied thereto in the sequence. Additionally, if the algorithmic process is not selected...

...process and then to a function block 100 to apply the algorithmic process to the **desired** set of data and then to a decision block 102 to determine whether additional sets...

...cut data in the data-set which then must be filled in by the appropriate **time** merge **operation** utilizing **extrapolation** , **interpolation** , etc. **techniques** . FIGURE 7a shows the raw data. FIGURE 7b shows the use of the cut data region **tool** 115. FIGURE 7b shows the points 108 and 110 highlighted by dots showing them as...

...appear as red. FIGURE 7d shows a vertical cut of the data, cutting across several **variables** simultaneously. Applying this causes all of the data points to be marked as cut, as...

...by a set of boundaries 112, which results are utilized to block out data. For **example** , if it were determined that data during a certain time period was invalid due to...

...for removing data, this is referred to as a manual manipulation of the data. However, **algorithms** can be applied to the data to change the **value** of that data. Each time the data is changed, it is rearranged in the spreadsheet...

...the various cutting tools and modify the stored data in accordance with these manipulations. For **example** , a **tool** could be utilized to manipulate multiple **variables** over a **given** time range to delete all of that data from the input database and reflect it...

...data set. The program then flows to a decision block 119 to determine if the **variables** have been selected and manipulated for display. If not, the program flows along an "N...

...display type and then to a function block 123 to display the data in the **desired** format. ...line back to the output of decision block 119 to determine if all of the **variables** have been selected. However, if the data is still in the modification stage, the program...

...from decision block 125 back to the input of decision block 119.
Once all the **variables** have been selected and displayed, the program flows from decision block 119 along a "Y...

...this display, which display is comprised of a first numerical template 114, that provides a **numerical** keypad function. A window 116 is provided that displays the **variable** that is being operated on. The **variables** that are available are illustrated in a window 118 which illustrates the various **variables** . In this **example** , the various **variables** are arranged in groups, one group illustrating a first date and time and a second...

...date and time. This is prior to time merging. The illustrated window 118 has the **variables** templ and press 1 and the **variable** press2, it being noted that press2 is on a different time scale than templ. A...

...122 is provided that allows selection of various mathematical functions, logical functions, etc.
In the **example** illustrated in FIGURE 8, the **variable** tempi is selected to be processed and provide the **logarithmic** function thereof. In this manner, the **variable** temp 1 is first selected from window 118 and then the logarithmic function "LOG" is...

...the window 122. The left parentheses is then selected, followed by the selection of the **variable** templ from window 118 and then followed by the selection of the right parentheses from window 120. This results in the selection of an **algorithmic** process which comprises a **logarithm** of the **variable** templ. This is then stored as a sequence, such that upon running the data through the run time sequence, data associated with the **variable** temp 1 has the **logarithmic** function applied thereto prior to inputting to the run time system model 26. This operation...

...After the data has been manually preprocessed, the algorithmic processes are applied thereto. In the **example** described above with reference to FIGURE 8, the **variable** tempi was processed by taking a **logarithm** thereof. This would result in a variation of the set of data associated with the **variable** temp 1. This is illustrated in Table 2. The sequence of operation associated therewith would...

...utilized. To perform this, the display of FIGURE 8 is again pulled up, and the **algorithmic** process selected. One **example** would be to take the **variable** temp 1 after time merge and add a **value** of 5000 to this

variable . This would result in each **value** in the column associated with the **variable** tempi being **increased** by that **value** . This would result in the data in ...is monitored at some point by flow meter 130, the flow meter 130 providing a **variable** output flowl. The flow continues to a process block 132, wherein various plant processes are...

...this process block. The process then flows to a temperature gauge 134 to output a **variable** templ. The process then flows to a process block 136 to perform other plant processes...

...receiving plant inputs. The process then flows to a pressure gauge 138, this outputting a **variable** press 1. The process continues with various other process blocks 140 and other **parameter** measurement blocks 140. This results in an overall plant output 142 which is the **desired** plant output. It can be seen that numerous processes occur between the output of **parameter** flowl and the plant output 142. **Additionally** , other plant outputs such as pressl and tempi occur at different stages in the process. This results in delays between a measured **parameter** and an effect on the plant output.

Referring now to FIGURE 10, there is illustrated a timing diagram illustrating the various effects of the output **variables** from the plant and the plant output. The output **variable** flowl experiences a change at a point 144.

Similarly, the output **variable** tempi experiences a change at a point 146 and the **variable** pressl experiences a change at a point 148. However, the corresponding change in the output is not time synchronous with the changes in the **variables** . Referring to the diagram labelled OUTPUT, changes in the plant output occur at points 150, 152 and 154, for the respective changes in the **variables** at points 144-148, respectively. The change between points 144 and 150 and the **variable** flowl and the output, respectively, experience a delay D2. The change in the output of point 152 associated with the change in the **variable** tempi occurs after delay D3. Similarly, the change in the output of point 154 associated with the change in the **variable** press 1 occurs after a delay of D1. In accordance with one aspect of the present invention, these delays are accounted for during **training** , and; subsequently, during the run time operation, these delays are also accounted for.

Referring now to FIGURE 11, there is illustrated a diagrammatic view of the delay for a **given** input **variable** x1))(t). It can be seen that a delay D is introduced to the system...

...t - D), this output is then input to the network. As such, the measured plant **variables** now coincide in time with the **actual** effect that is realized in the measured output such that, during **training** , a system model can be trained with a more accurate representation of the system.

Referring...

...the delay. Rather than provide an additional set of data for each delay that is **desired** , x(t+(tau)), **variable** length buffers are provided in each data set after preprocessing, the length of which corresponds...

...is provided which is selected as a tap output of the buffer 160 with a **value** of (tau) = 2. This results in the overall delay inputs to the **training** model 20. Additionally, these delays are stored as delay settings for use during the run...

...provided to the operator for selecting the various delays to be applied

to the input **variables** and the output **variables** utilized in **training** . In this **example** , it can be seen that by selecting a delay for the **variable** tempi of -4.0, -3.50 and -3.00, three separate input **variables** have not been selected for input to the **training** model 20. Additionally, three separate outputs have been selected, one for delay 0.00, one...

...0.50 and one for a delay of 1.00 to predict present and future **values** of the **variable** . Each of these can be processed to vary the absolute **value** of the delays associated with the input **variables** . It can therefor be seen that a maximum buffer of -4.0 for an output...

...that it is not necessary to completely replicate the data in any of the delayed **variable** columns as a separate column, thus **increasing** the amount of memory utilized.

Referring now to FIGURE 14, there is illustrated a block...

...delays. A buffer 170 is illustrated having a length of N, which receives an input **variable** xn))'(t) from the preprocessor 12 to provide on the output thereof an output xnD))(t) as a delayed input to the **training** model 20. A multiplexer 172 is provided which has multiple inputs, ...a (tau)-select circuit 174 provided for selecting which of the taps to output. The **value** of (tau) is a function of other **variables** **parameters** such as temperature, pressure, flow rates, etc. For **example** , it may have been noted empirically that the delays are a function of temperature. As such, the temperature relationship could be placed in the block 74 and then the external **parameters** input and the **value** of (tau) utilized to select the various taps input to the multiplexer 172 for output...

...the various delay settings and functional relationships of the delay with respect to the external **parameters** are stored in the storage area 18. The external **parameters** can then be measured and the **value** of (tau) selected as a function of this temperature and the functional relationship provided by the information stored in the storage area 18. This is to be compared with the **training** operation wherein this information is externally input to the system. For **example** , with reference to FIGURE 13, it could be noticed that all of the delays for the **variable** temp must be shifted up by a **value** of 0.5 when the temperature reached a certain point. With the use of the...

...described with respect to FIGUREs 12 and 14, it is only necessary to vary the **value** of the control input to the multiplexers 172 associated with each of the **variables** , it being understood that in the **example** of FIGURE 13, three multiplexers 172 would be required for the **variable** templ, since there are three separate input **variables** .

Referring now to FIGURE 15a, there is illustrated a block diagram of the preprocessing system for setting the delay **parameters** , which delay **parameters** are learned. For simplicity purposes, the preprocessing system is not illustrated; rather, a table 176...

...is achieved by a time delay adjustor 178, which time delay adjustor utilizes the stored **parameters** in a delayed **parameter** block 18'. The delay **parameter** block 18' is similar to the delay setting block 18, with the exception that absolute...

...contained therein. Rather, information relating to a window of data is stored in the delay **parameter** block 18'. The time delay adjustor 178 is

operable to select a window of data...

...each of the sets of data x1))' - xn))' and convert this information into a single **value** for output therefrom as an input **value** in, - inn)). These are directly input to a system model 26', which system model 26' is similar to the run-time system model 26 and the **training** model 20 in that it is realized with a non-linear **neural network** . The non-linear **neural network** is illustrated as having an input layer 179, a hidden layer 180 and an output...

...table 176 to the input layer 179. This mapping function is dependent upon the delay **parameters** in the delay **parameter** block 18'. As will be described hereinbelow, these **parameters** are learned under the control of a learning module 183, which learning module 183 is controlled during the network **training** in the **training** mode. It is similar to that described above with respect to FIGURE 1a.

During learning...

...183 is operable to control both the time delay adjustor block 178 and the delay **parameter** block 18' to change the **values** thereof in **training** of the system model 26'. During **training** , target outputs are input to the output layer 182 and a set of **training** data input thereto in the form of the chart 176, it being noted that this is already preprocessed in accordance with the operation as described hereinabove. The model **parameters** of the system model 26' stored in the storage area 22 are then adjusted in accordance with a **predetermined training** algorithm to minimize the error. However, the error can only be minimized to a certain extent for a **given** set of delays. Only by setting the delays to their optimum **values** will the error be minimized to the maximum extent. Therefore, the learning module 183 is operable to vary the **parameters** in the delay **parameter** block 18' that are associated with the timing delay adjustor 178 in order to further...

...as Ci))((tau)i)), (alpha)i)), (beta)i))). Therefore, each of the data columns is **parameterized** via three numbers, the time lag **value** (tau)i)), the leading edge time-rise width (alpha)i)) and the trailing edge width (beta)i)). The inputs to the **neural network** representing the system model 26' would then be the convolution of this time-lag window and the data from the taps from the associated column. The input **value** would be as follows:

Or, the discretely: where, e.g., **Equation** 4 represents a Gaussian window. **Given** this function for each of the inputs, the network can then learn on the **parameters** (tau)i)), (alpha)i)) and (beta) ...To achieve the above learning, an error function is required. This error function utilizes the **neural network** error function as follows: where the **value** y(j) is the target of the network and the **value** o(j) is the output of the net and NPATS)) is the number of **training patterns** . The output of the network is dependent on several **parameters** : where, Wkl)) is the matrix of **neural network** weights, learned by gradient descent: and Ci)) is the convolution window with **parameters** (tau)i)), (alpha)i)) and (beta)i)) are also learned by gradient descent; that is...

...more slowly than Wkl)). That is, (eta)w)) is approximately equal to ten times the **value** of (eta)(tau))) and (eta)(tau))) is approximately equal to (eta)(alpha))) and is approximately...

...error.

Referring now to FIGURE 16, there is illustrated a schematic view of a conventional **neural network** utilized for the **training** model 20 and for the run time system model 26. The **neural network** is a multi-layer network comprised of a plurality of input nodes 186 and a...

...each of the output nodes 188 or select ones thereof. The weighted interconnections and the **values** thereof define the stored representation, and these weights are the **values** that are learned during the **training** operation. In general, the learning operation comprises target data input to the output nodes 188, which are utilized for a compare operation and then a **training** algorithm, such as a back propagation technique is utilized, as illustrated by block 192. This...
...will be described hereinbelow, this network is trained through any one of a number of **training** algorithms and architectures such as **Radial Basis Functions** , Gaussian Bars, or conventional Backpropagation techniques. The Backpropagation learning technique is generally described in D...

...which document is incorporated herein by reference. In this type of algorithm, a set of **training** data is input to the input layer 186 to generate an output, which output in...

...error back propagated from the output layer 188 to the input layer 186 with the **values** of the weights on the input interconnect layer and the output interconnect layer changed in accordance with the gradient descent technique. Initially, the error is very large, but as **training** data is sequentially applied to the input, and this compared to corresponding target output data...

...FIGURE 17, there is illustrated a flowchart illustrating the determination of time delays for the **training** operation. This flowchart is initiated at a block 198 and then flows to a function...

...to FIGURE 13. The program then flows to a decision block 202 to determine whether **variable** Is are to be selected. The program flows along a "Y" path to a function block 204 to receive an external input and vary the **value** of (tau) in accordance with the relationship selected by the operator, this being a manual operation in the **training** mode. The program then flows to a decision block 206 to determine whether the **value** of (tau) is to be learned by an adaptive **algorithm** . If **variable** (tau)s are not to be selected in the decision block 202, the program then flows around the function block 204 along the "N" path thereof.

If the **value** of (tau) is to be learned adaptively, the program flows from the decision block 206 to a function block 208 to learn the **value** of (tau) adaptively. The program then flows to a function block 210 to save the **value** of (tau). If no adaptive learning is required, the program flows from the decision block 206 along the "N" path to function block 210. After the (tau) **parameters** have been determined, the model 20 is trained, as indicated by a function block 212 and then the **parameters** stored, as indicated by a function block 214 and then the program flows to a...block 236.

Function block 236 flows to a decision block 238 to determine whether the **value** of (tau) is to be varied. If so, the program flows to a function block 240 to set the **value** of (tau) **variably** , then to the input of a function block 242 and, if not, the program flows...
...run time inputs and then flows to a function block 244 to load the model **parameters** . The program then flows to a function block 246 to process

the generated inputs through...

...now to FIGURE 19, there is illustrated a flowchart for the operation of setting the **value** of (tau) **variably** . The program is initiated at a block 252 and then proceeds to a function block 254 to receive the external control input. The **value** of (tau) is varied in accordance with the relationship stored in the storage area 14...

...The data is then preprocessed in the preprocess block 34 in accordance with the preprocess **parameters** stored in the storage area 14. The data is then delayed in the delay block...

...this delay block 18 also receiving the external block control input, which is comprised of **parameters** on which the **value** of (tau) depends to provide the **variable** setting operation that was utilized during the **training** mode. The output of the delay block is then input to a selection block 260...

...a control model 264 is provided. Both models 262 and 264 are identical to the **training** model 20 and utilize the same **parameters** ; that is, models 262 and 264 have stored therein a representation of the system that was trained in the **training** model 20. The predictive system model 262 provides on the output thereof a predictive output...

...DCS 24.

In summary, there has been provided a system for preprocessing data prior to **training** the model. The preprocessing operation is operable to provide a time merging of the data such that each set of input data is input to a **training** system model on a uniform time base. Furthermore, the preprocessing operation is operable to fill in missing or bad data. Additionally, after preprocessing, **predetermined** plant delays are associated with each of the **variables** to generate delayed inputs. These delayed inputs are then input to a **training** model and the **training** model trained in accordance with a **predetermined** **training** algorithm to provide a representation of the system. This representation is stored as model **parameters** . **Additionally** , the preprocessing **steps** utilized to preprocess the data are stored as a sequence of preprocessing **algorithms** and the delay **values** that are determined during **training** are also stored. A distributed control system that can be controlled to process the output **parameters** therefrom in accordance with the process **algorithms** and set delays in accordance with the **predetermined** delay settings. A predictive system model, or a control model, is then built on the stored model **parameters** and the delayed inputs input thereto to provide a predicted output. This predicted output provides...

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PREDICTIVE **NETWORKS AND** METHOD **WITH LEARNED PREPROCESSING** PARAMETERS
VORAUSSCHAUENDE NETZWERKE UND VERFAHREN MIT GELERNTEN VORARBEITUNGSPARAMETERS
RESEAUX PREDICTIFS **ET** METHODE **AVEC PARAMETRES DE PRETRAITEMENT APPRIS**
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Available Text	Language	Update	Word Count
CLAIMS B	(English)	200014	1393
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CLAIMS B	(French)	200014	1717
SPEC B	(English)	200014	10435
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PREDICTIVE **NETWORKS AND** METHOD **WITH LEARNED PREPROCESSING** PARAMETERS
RESEAUX PREDICTIFS **ET** METHODE **AVEC PARAMETRES DE PRETRAITEMENT APPRIS**

...SPECIFICATION processing of the data so as to account for time synchronization, time-delays, transforms and **variable** time-delays prior to input to a network for either **training** of the network or running of the network.

BACKGROUND OF THE INVENTION

A common problem that is encountered in **training neural networks** for prediction, forecasting, **pattern** recognition, sensor validation and/or processing problems is that some of the **training** /testing **patterns** might be missing, corrupted, and/or incomplete. Prior systems merely discarded data with the result that some areas of the input space may not have been covered during **training** of the **neural network** .

For **example** , if the network is utilized to learn the **behavior** of a chemical plant as a function of the historical sensor and **control settings** , these sensor readings are typically **sampled** electronically, entered by hand from gauge readings and/or entered by hand from laboratory results...

...a common occurrence that some or all of these readings may be missing at a **given** time. It is also common that the various **values** may be **sampled** on different time intervals. **Additionally** , any one **value** may be "bad" in the sense that after the **value** is entered, it may be determined by some method that a data item was, in...
...bad" or "missing" data. The "Swiss-cheese" data table described above occurs quite often in **real** -world problems.

Conventional **neural network training** and testing methods require complete **patterns** such that they are required to discard **patterns** with missing or bad data. The deletion of the bad data in this manner is an inefficient method for **training** a **neural network** . For **example** , suppose that a **neural network** has ten inputs and ten outputs, and also suppose that one of the inputs or outputs happens to be missing at the **desired** time for fifty percent or more of the **training patterns** . Conventional methods would discard these **patterns** , leading to **training** for those **patterns** during the **training** mode and no reliable predicted output during the run mode. This is inefficient, considering that for this case more than ninety percent of the information is still there for the **patterns** that conventional methods would discard. The predicted output corresponding to those certain areas will be...

...the overall data after screening bad or missing data. Additionally, experimental results have shown that **neural network** testing performance generally increases with more **training** data, such that throwing away bad or incomplete data decreases the overall performance of the **neural network** .

In addition to the above, when data is retrieved on different time scales, it is...

...the data on a common time scale. However, this is difficult in that for a **given** time scale, another and longer time scale results in missing data at that position. For **example** , if one set of data were taken on an hourly basis and another set of...

...all data is presented at synchronized times to the system model. Worse yet, the data **sample** periods may be non-periodic, producing totally asynchronous data.

In addition, this data may be...

...be able to read all of these different data formats, keeping track of the data **value** and the time-stamp of the data out to one or more "flat files" which are column oriented, each column corresponding to a data **variable** and/or the data/time stamp of the **variable** . It is a formidable task to retrieve this data keeping track of the date-time...

...aspect of data integrity is that with respect to inherent delays in a system. For **example** , in a chemical processing system, a flow meter output can provide data at time t0)) at a **given value** . However, a **given** change in flow resulting in a different reading on the flow meter may not affect the output for a **predetermined** delay (tau). In order to predict what the output would be, this flow meter output...

...network at a delay equal to (tau). This must also be accounted for in the **training** of the network. In generating data that accounts for time delays, it has been postulated...

...original data, wherein only the delayed data is utilized. Further, in order to change the **value** of the delay, an entirely new set of input data must be generated off the original set.

The document **NEURAL NETWORKS** , vol. 4, no. 2, 1991, OXFORD, GB, pages 185 - 191; LEVIN ' **Neural network** architecture for adaptive system modeling and control' discloses a computing architecture for adaptive control and system modeling based on nonlinear discrete **neural networks** , which are massively parallel and have distributed structures for signal processing, with the potential of dynamical learning. The document proposes a delayed-input, delayed-state network architecture and its general **training** scheme. A solution for the problem of analog signals representation is suggested therein. In this document, the output of a **neural network** acting as a plant controller ...respectively. According to a first embodiment the network includes a data storage device for storing **training** data from a runtime system. The network operates in two modes, a runtime mode and a **training** mode. In the runtime mode, runtime data is received from the runtime system and, in the **training** mode, data is retrieved from the data storage device, the **training** data being both **training** input data and **training** output data. A data preprocessor is provided for preprocessing received data in accordance with **predetermined** preprocessing **parameters** to output preprocessed data. A network is provided having an input for receiving the preprocessed...

...an output through a stored representation of the runtime system in accordance with associated model **parameters** . A **control device** controls the data preprocessor to operate in either the **training** mode or the runtime mode. In the runtime mode, the preprocessor is operable to process the stored **training** data and output preprocessed **training** data. In the runtime mode, the preprocessor is operable to preprocess runtime data received from the runtime system to output preprocessed runtime data. A **training** device is operable in the **training** mode to train the network on the **training** data in accordance with a **predetermined training algorithm** to define the model **parameters** on which the network operates such that the network operates in the runtime mode to...

...another embodiment of the present invention, an input device is provided for determining the preprocessing **parameters** in accordance with **predetermined** criteria. A **parameter** storage device is operable to store the determined preprocessing **parameters** after determination by the input device. The data preprocessor is controlled by the **control device** to select the determined preprocessing **parameters** from the **parameter** storage device in the runtime mode and, in the **training** mode, the data preprocessor is controlled by the input device and the determined preprocessing **parameters** generated thereby.

In yet another embodiment of the present invention, the data preprocessor is comprised...

...data being on different time scales. A time merge device is operable to select a **predetermined** time scale and reconcile the received data such that all the received data is placed...

...preprocessed data. The data preprocessor further includes a pre-time merge processor for applying a **predetermined** algorithm to the received data prior to input to the time merge device. A post-time merge processor is provided for applying a **predetermined** algorithm to the data output by the time merge device prior to output as the...

...selective delay applied thereto prior to input to the network in both the runtime and **training** modes.

BRIEF DESCRIPTION OF THE DRAWINGS

For a more complete understanding of the present invention...

...1 illustrates an overall block diagram of the system for both preprocessing data during the **training** mode and for preprocessing data during the run mode;

FIGURE 1a illustrates a simplified block...

...of FIGURE 1;

FIGURE 2 illustrates a detailed block diagram of the preprocessor in the **training** mode;

FIGURE 3 illustrates a simplified block diagram of the time merging operation, which is...

...a block diagram of a plan depicting the various places in the process flow that **parameters** occur relative to the plant output;

FIGURE 10 illustrates a diagrammatic view of the relationship between the various plant **parameters** and the plant output;

FIGURE 11 illustrates a diagrammatic view of the delay provided for input data **patterns** ;

FIGURE 12 illustrates a diagrammatic view of the buffer formation for each of the network...

...the display for selection of the delays associated with various inputs and outputs in the **neural** **network** model;

FIGURE 14 illustrates a block diagram for a **variable** delay selection;

FIGURE 15a illustrates a block diagram of the adaptive determination of the delay;

FIGURE 15b illustrates **examples** of the time-delay functions used in adaptive or **variable** time-delay modes;

FIGURE 16 illustrates a diagrammatic view of a conventional multi-layer **neural** **network** ;

FIGURE 17 illustrates a flowchart depicting the time delay operation;

FIGURE 18 illustrates a flowchart depicting the run mode operation;

FIGURE 19 illustrates a flowchart for setting the **value** of the **variable** delay; and

FIGURE 20 illustrates a block diagram of the interface of the run time ...

...there is illustrated an overall block diagram of the data preprocessing operation in both the **training** mode and the run time mode. In the **training** mode, one of more data files 10 are provided, which data files include both input **training** data and output **training** data. The **training** data is arranged in "sets", which sets correspond to different plant **variables** , and which may be **sampled** at different time intervals. This data is referred to as the "raw" data. When the...done in such a manner as to keep track of the time stamp for each **variable** . Thus, the "raw" data is organized as time, **value** pairs of columns; that

is, for each **variable** xi)), there is its associated time of **sample** ti)). The data can then be grouped into sets (xi)), ti))).
If any of the...

...data will be grouped in common time scale groups, and data that is on, for **example** , a fifteen minute **sample** time scale will be grouped together and data **sampled** on a one hour **sample** time scale will be grouped together. However, any type of format that provides viewing of...

...hereinbelow. During operation, the preprocessor 12 is operable to store various preprocessing algorithms in a **given** sequence in a storage area 14. As will be described hereinbelow, the sequence defines the...

...data. This operation can be performed on both the target output data and the input **training** data. The delay settings are stored in a storage area 18 after determination thereof.
The output of the delay block 16 is input to a **training** model 20. The **training** model 20 is a non-linear model that receives input data and compares it with...

...for predicting the target output data from the input data. In the preferred embodiment, the **training** model utilizes a multi-layered **neural network** that is trained on one of multiple methods, one being Back Propagation. Various weights within the network are set during the Back Propagation **training** operation, and these are stored as model **parameters** in a storage area 22. The **training** operation and the **neural network** are conventional systems.
A Distributed Control System (DCS) 24 is provided that is operable to generate various system measurements and **control settings** representing system **variables** such as temperature, flow rates, etc., that comprise the input data to a system model...

...inputs to the DCS 24. The run time system model 26 is utilizing the model **parameters** stored in the storage area 22. It should be noted that the run time system model 26 contains a representation learned during the **training** operation, which representation was learned on the preprocessed data. Therefore, data generated by the DCS...

...sequence of preprocessing algorithms stored in the storage area 14, which were generated during the **training** operation. The output of the run time preprocessor 34 is input to a run time...

...the preprocessor 34', the delay 36' and the system model 26' operate in both a **training** mode and a run-time mode. A multiplexer 35 is provided that receives the output...

...the data file(s) 10 and the output of the DCS 24, this providing plant **variables** of the DCS 24, the output of the multiplexer input to the preprocessor 34'. A **control device** 37 is provided that controls the multiplexer 35 to select either a **training** mode or a run-time mode. In the **training** mode, the data file(s) 10 has the output thereof selected by a multiplexer and the preprocessor 34' is operable to preprocess the data in accordance with a **training** mode, i.e., the preprocessor 34' is utilized to determine what the **predetermined** algorithm sequence is that is stored in the storage area 14. An input/output device I/O 41 is provided for allowing the operator to interface with the **control device** 37. The delay 36' is also controlled by the **control device** 37

to determine the delay settings for storage in the storage area 18. The system model 26' is operated in a **training** mode such that the target data and the input data to the system model 26' are generated, the **training** controlled by **training** block 39. The **training** block 39 is operable to select one of multiple **training** algorithms, such as back propagation, for **training** of the system model 26'. The model **parameters** are stored in the storage area 22.

After **training** , the **control device** 37 places the system in a run-time mode such that the preprocessor 34' is...

...there is illustrated a more detailed block diagram of the preprocessor 12 utilized during the **training** mode. In general, there are three stages to the preprocessing operation. The central operation is...

...is operable to store the sequence of the various processes that are determined during the **training** mode, these interfaced with a bi-directional bus 60. During the **training** mode, the controller 46 determines which of the functional algorithms are to be applied to...

...seen that the waveform associated with xl))(t) has only a certain number, n, of **sample** points associated therewith. The time-merge operation is a transform that takes one or more columns of data, xi))(ti))), such as that shown in FIGURE 4a, with ni)) time **samples** at times ti))'. That is, the time-merge operation is a function, (OMEGA), that produces a new set of data (x') on a new time sale t' from the **given** set of data x(t) **sampled** at t. This function is done via a variety of conventional extrapolation, interpolation, or box...

...as a C-language callable function as: where xi)), ti)) are vectors of the old **values** and old times; xi))'. . . xk))' are vectors of the new **values** ; and t' is the new time-scale vector.

Referring now to FIGURE 5a, there is...

...The data table consists of data with time disposed along a vertical scale and the **samples** disposed along a horizontal scale. Each **sampl**e comprises many different pieces of data with two data intervals illustrated. It can be seen that when the data is examined for both the data **sampled** at the time interval "1" and the data **sampled** at the time interval "2", that some portions of the data result in incomplete **patterns** . This is illustrated by a dotted line 63, where it can be seen that some data is missing in the data **sampled** at time interval "1" and some is missing in time interval "2". A complete **neural network pattern** is illustrated box 64, where all the data is complete. Of interest is the time difference between the data **sampled** at time interval "1" and the data **sampled** at time interval "2". In time interval "1", the data is essentially present for all steps in time, whereas data **sampled** at time interval "2" is only **sampled** periodically relative to data **sampled** at time interval "1". As such, a data reconciliation procedure is implemented that fills in the missing data and also reconciles between the time **samples** in time interval "2" such that the data is complete for all time **samples** for both time interval "1" and time interval "2".

The **neural network** models that are utilized for time-series prediction and control require that the time-interval between successive **training patterns** be constant. Since the data that comes in from **real** -world systems is not always on the same time scale, it is desirable to time-merge the data before it can be used for **training** or running the

neural network model. To achieve this time-merge operation, it may be necessary to extrapolate, interpolate, average...

...the data in each column over each time-region so as to give an input **value** x'(t) that is on the appropriate time-scale. All of these are referred to...

...algorithm utilized may include linear estimates, spline-fit, boxcar algorithms, etc. If the data is **sampled** too frequently in the time-interval, it will be necessary to smooth or average the data to get a **sample** on the **desired** time scale. This can be done by window averaging techniques, sparse- **sample** techniques or spline techniques.

In general, x'(t) is a function of all of the raw **values** x(t) **given** at present and past times up to some maximum past time, Xmax. That is, where some of the **values** of xi))(tj))) may be missing or bad.

This method of finding x'(t) using past **values** is strictly extrapolation. Since the system only has past **values** available during runtime mode, the **values** must be reconciled. The simplest method of doing this is to take the next extrapolated **value** x'i))(t) = xi))(tN))); that is, take the last **value** that was reported. More elaborate extrapolation **algorithms** may use past **values** xi))(t-(tau)ij))), jet(o, ... imax))). For **example** , linear extrapolation would use: Polynomial, spline-fit or **neural - network** extrapolation techniques use Equation 3. (See eg. W.H. Press, "Numerical Recipes", Cambridge University Press (1986), pp. 77-101) **Training** of the neural net would **actually** use interpolated **values** , i.e., **Equation** 4, wherein the case of interpolation tN))>t.

Referring now to FIGURE 5b, there is illustrated an input data **pattern** and target output data **pattern** illustrating the pre-process operation for both preprocessing input data to provide time merged output...

...also pre-processing the target output data to provide pre-processed target output data for **training** purposes. The data input x(t) is comprised of a vector with many inputs, x1...

...or interpolated to insure that all data is present on a single time scale. For **example** , if the data at x1))(t) were on a time scale of one **sample** every second, a **sample** represented by the time tk)), and the output time scale were **desired** to be the same, this would require time merging the rest of the data to...

...it is illustrated as being synchronized. The data buffer in FIGURE 4b is illustrated in **actual** time. The reconciliation could be as simple as holding the last **value** of the input x2))(t) until a new **value** is input thereto, and then discarding the old **value** . In this manner, an output will always exist. This would also be the case for...

...on one time scale and the data x2))(t) is on a different time scale. **Additionally** , one **value** of the data set x1))(t) is illustrated as being bad, which piece of bad...

...the preprocessing mode fills in this bad data and then time merges it. In this **example** , the time scale for x1))(t) is utilized as a time scale for the time...

...the time merge data x1))'(t) is on the same time scale with the "cut" **value** filled in as a result of the preprocessing operation and the data set x2))(t...

...manually preprocess the data. In manual preprocessing of data, the data is viewed in a **desired** format by the operator and the operator can look at the data and eliminate, "cut" or otherwise modify obviously bad data **values** . This is to be compared to the automatic operation wherein all **values** are subjected to a **predetermined** **algorithm** to process the data. For **example** , if the operator noticed that one data **value** is significantly out of range with the normal **behavior** of the remaining data, this data **value** can be "cut" such that it is no longer present in the data set and...

...However, an algorithm could be generated that either cuts out all data above a certain **value** or clips the **values** to a **predetermined** maximum. The clipping to a **predetermined** maximum is an algorithmic operation that is ...Y" block to a function block 80 to select a particular algorithmic process for a **given** set of data. After selecting the algorithmic process, the program flows to a function block...

...function block 80 along a "Y" path. Once all data has been subjected to the **desired** algorithmic processes, the program flows along a "N" path from decision block 84 to a...

...86 to store the sequence of algorithmic processes such that each data set has the **desired** algorithmic processes applied thereto in the sequence. Additionally, if the algorithmic process is not selected...

...process and then to a function block 100 to apply the algorithmic process to the **desired** set of data and then to a decision block 102 to determine whether additional sets...

...cut data in the data-set which then must be filled in by the appropriate **time** merge **operation** utilizing **extrapolation** , **interpolation** , etc. **techniques** . FIGURE 7a shows the raw data. FIGURE 7b shows the use of the cut data region **tool** 115. FIGURE 7b shows the points 108 and 110 highlighted by dots showing them as...

...appear as red. FIGURE 7d shows a vertical cut of the data, cutting across several **variables** simultaneously. Applying this causes all of the data points to be marked as cut, as...

...by a set of boundaries 112, which results are utilized to block out data. For **example** , if it were determined that data during a certain time period was invalid due to...

...for removing data, this is referred to as a manual manipulation of the data. However, **algorithms** can be applied to the data to change the **value** of that data. Each time the data is changed, it is rearranged in the spreadsheet...

...the various cutting tools and modify the stored data in accordance with these manipulations. For **example** , a **tool** could be utilized to manipulate multiple **variables** over a **given** time range ...data set. The program then flows to a decision block 119 to determine if the **variables** have been selected and manipulated for display. If not, the program flows along an "N...

...display type and then to a function block 123 to display the data in the

desired format. The program then flows to a decision block 125 to indicate the operation wherein...

...line back to the output of decision block 119 to determine if all of the **variables** have been selected. However, if the data is still in the modification stage, the program...
...from decision block 125 back to the input of decision block 119.
Once all the **variables** have been selected and displayed, the program flows from decision block 119 along a "Y...

...this display, which display is comprised of a first numerical template 114, that provides a **numerical** keypad function. A window 116 is provided that displays the **variable** that is being operated on. The **variables** that are available are illustrated in a window 118 which illustrates the various **variables** . In this **example** , the various **variables** are arranged in groups, one group illustrating a first date and time and a second...

...date and time. This is prior to time merging. The illustrated window 118 has the **variables** temp1 and press1 and the **variable** press2, it being noted that press2 is on a different time scale than temp1. A...

...122 is provided that allows selection of various mathematical functions, logical functions, etc.
In the **example** illustrated in FIGURE 8, the **variable** temp1 is selected to be processed and provide the **logarithmic** function thereof. In this manner, the **variable** temp1 is first selected from window 118 and then the **logarithmic** function "LOG" is selected from the window 122. The left parentheses is then selected, followed by the selection of the **variable** temp1 from window 118 and then followed by the selection of the right parentheses from window 120. This results in the selection of an **algorithmic** process which comprises a **logarithm** of the **variable** temp1. This is then stored as a sequence, such that upon running the data through the run time sequence, data associated with the **variable** temp1 has the **logarithmic** function applied thereto prior to inputting to the run time system model 26. This operation...

...After the data has been manually preprocessed, the algorithmic processes are applied thereto. In the **example** described above with reference to FIGURE 8, the **variable** temp1 was processed by taking a **logarithm** thereof. This would result in a variation of the set of data associated with the **variable** temp1. This is illustrated in Table 2.
The sequence of operation associated therewith would define...utilized. To perform this, the display of FIGURE 8 is again pulled up, and the **algorithmic** process selected. One **example** would be to take the **variable** temp1 after time merge and add a **value** of 5000 to this **variable** . This would result in each **value** in the column associated with the **variable** temp1 being **increased** by that **value** . This would result in the data in Table 4.
The sequence would then be updated...
...is monitored at some point by flow meter 130, the flow meter 130 providing a **variable** output flow1. The flow continues to a process block 132, wherein various plant processes are...

...this process block. The process then flows to a temperature gauge 134 to output a **variable** temp1. The process then flows to a process block 136 to perform other plant processes...

...receiving plant inputs. The process then flows to a pressure gauge 138, this outputting a **variable** press1. The process continues with various other process blocks 140 and other **parameter** measurement blocks 140. This results in an overall plant output 142 which is the **desired** plant output. It can be seen that numerous processes occur between the output of **parameter** flow1 and the plant output 142. **Additionally** , other plant outputs such as press1 and temp1 occur at different stages in the process. This results in delays between a measured **parameter** and an effect on the plant output.

Referring now to FIGURE 10, there is illustrated a timing diagram illustrating the various effects of the output **variables** from the plant and the plant output. The output **variable** flow1 experiences a change at a point 144. Similarly, the output **variable** temp1 experiences a change at a point 146 and the **variable** press1 experiences a change at a point 148. However, the corresponding change in the output is not time synchronous with the changes in the **variables** . Referring to the diagram labelled OUTPUT, changes in the plant output occur at points 150, 152 and 154, for the respective changes in the **variables** at points 144-148, respectively. The change between points 144 and 150 and the **variable** flow1 and the output, respectively, experience a delay D2. The change in the output of point 152 associated with the change in the **variable** temp1 occurs after delay D3. Similarly, the change in the output of point 154 associated with the change in the **variable** press1 occurs after a delay of D1. In accordance with one aspect of the present invention, these delays are accounted for during **training** , and, subsequently, during the run time operation, these delays are also accounted for.

Referring now to FIGURE 11, there is illustrated a diagrammatic view of the delay for a **given** input **variable** x1))(t). It can be seen that a delay D is introduced to the system...

...t - D), this output is then input to the network. As such, the measured plant **variables** now coincide in time with the **actual** effect that is realized in the measured output such that, during **training** , a system model can be trained with a more accurate representation of the system.

Referring...

...the delay. Rather than provide an additional set of data for each delay that is **desired** , x(t+(tau)), **variable** length buffers are provided in each data set after preprocessing, the length of which corresponds...

...is provided which is selected as a tap output of the buffer 160 with a **value** of (tau) = 2. This results in the overall delay inputs to the **training** model 20. Additionally, these delays are stored as delay settings for use during the run...provided to the operator for selecting the various delays to be applied to the input **variables** and the output **variables** utilized in **training** . In this **example** , it can be seen that by selecting a delay for the **variable** temp1 of -4.0, -3.50 and -3.00, three separate input **variables** have not been selected for input to the **training** model 20. Additionally, three separate outputs have been selected, one for delay 0.00, one...

...0.50 and one for a delay of 1.00 to predict present and future **values** of the **variable** . Each of these can be processed to vary the absolute **value** of the delays associated with the input **variables** . It can therefor be seen that a maximum buffer of -4.0 for an output...

...that it is not necessary to completely replicate the data in any of the

delayed **variable** columns as a separate column, thus **increasing** the amount of memory utilized.

Referring now to FIGURE 14, there is illustrated a block...

...delays. A buffer 170 is illustrated having a length of N, which receives an input **variable** xn))'(t) from the preprocessor 12 to provide on the output thereof an output xnD))(t) as a delayed input to the **training** model 20. A multiplexer 172 is provided which has multiple inputs, one from each of...

...a (tau)-select circuit 174 provided for selecting which of the taps to output. The **value** of (tau) is a function of other **variables** **parameters** such as temperature, pressure, flow rates, etc. For **example** , it may have been noted empirically that the delays are a function of temperature. As such, the temperature relationship could be placed in the block 74 and then the external **parameters** input and the **value** of (tau) utilized to select the various taps input to the multiplexer 172 for output...

...the various delay settings and functional relationships of the delay with respect to the external **parameters** are stored in the storage area 18. The external **parameters** can then be measured and the **value** of (tau) selected as a function of this temperature and the functional relationship provided by the information stored in the storage area 18. This is to be compared with the **training** operation wherein this information is externally input to the system. For **example** , with reference to FIGURE 13, it could be noticed that all of the delays for the **variable** templ must be shifted up by a **value** of 0.5 when the temperature reached a certain point. With the use of the...

...described with respect to FIGUREs 12 and 14, it is only necessary to vary the **value** of the control input to the multiplexers 172 associated with each of the **variables** , it being understood that in the **example** of FIGURE 13, three multiplexers 172 would be required for the **variable** templ, since there are three separate input **variables** .

Referring now to FIGURE 15a, there is illustrated a block diagram of the preprocessing system for setting the delay **parameters** , which delay **parameters** are learned. For simplicity purposes, the preprocessing system is not illustrated; rather, a table 176...

...is achieved by a time delay adjustor 178, which time delay adjustor utilizes the stored **parameters** in a delayed **parameter** block 18'. The delay **parameter** block 18' is similar to the delay setting block 18, with the exception that absolute...

...contained therein. Rather, information relating to a window of data is stored in the delay **parameter** block 18'. The time delay adjustor 178 is operable to select a window of data...

...each of the sets of data x1))' - xn))' and convert this information into a single **value** for output therefrom as an input **value** in1)) - inn)). These are directly input to a system model 26', which system model 26' is similar to the run-time system model 26 and the **training** model 20 in that it is realized with a non-linear **neural network** . The non-linear **neural network** is illustrated as having an input layer 179, a hidden layer 180 and an output...

...table 176 to the input layer 179. This mapping function is dependent

upon the delay **parameters** in the delay **parameter** block 18'. As will be described hereinbelow, these **parameters** are learned under the control of a learning module 183, which learning module 183 is controlled during the network **training** in the **training** mode. It is similar to that described above with respect to FIGURE 1a.

During learning...

...183 is operable to control both the time delay adjustor block 178 and the delay **parameter** block 18' to change the **values** thereof in **training** of the system model 26'. During **training** , target outputs are input to the output layer 182 and a set of **training** data input thereto in the form of the chart 176, it being noted that this is already preprocessedin accordance with the operation as described hereinabove. The model **parameters** of the system model 26' stored in the storage area 22 are then adjusted in accordance with a **predetermined** **training** algorithm to minimize the error. However, the error can only be minimized to a certain extent for a **given** set of delays. Only by setting the delays to their optimum **values** will the error be minimized to the maximum extent. Therefore, the learning module 183 is operable to vary the **parameters** in the delay **parameter** block 18' that are associated with the timing delay adjustor 178 in order to further...

...as Ci))((tau)i)), (alpha)i)), (beta)i))). Therefore, each of the data columns is **parameterized** via three numbers, the time lag **value** (tau)i)), the leading edge time-rise width (alpha)i)) and the tailing edge width (beta)i)). The inputs to the **neural** **network** representing the system model 26' would then be the convolution of this time-lag window and the data from the taps from the associated column. The input **value** would be as follows: Or, the discretely: where, e.g., **Equation** 4 represents a Gaussian window. **Given** this function for each of the inputs, the network can then learn on the **parameters** (tau)i)),(alpha)i)) and (beta)i)).

To achieve the above learning, an error function is required. This error function utilizes the **neural** **network** error function as follows: where the **value** y(j) is the target of the network and the **value** o(j) is the output of the net and NPATS)) is the number of **training** **patterns** . The output of the network is dependent on several **parameters** : where, Wkl)) is the matrix of **neural** **network** weights, learned by gradient descent: and Ci)) is the convolution window with **parameters** (tau)i)), (alpha)i)) and (beta)i)) are also learned by gradient descent; that is...

...more slowly than Wkl)). That is, (eta)w)) is approximately equal to ten times the **value** of (eta)(tau))) and (eta)(tau))) is approximately equal to (eta)(alpha))) and is approximately...

...error.

Referring now to FIGURE 16, there is illustrated a schematic view of a conventional **neural** **network** utilized for the **training** model 20 and for the run time system model 26. The **neural** **network** is a multi-layer network comprised of a plurality of input nodes 186 and a...

...each of the output nodes 188 or select ones thereof. The weighted interconnections and the **values** thereof define the stored representation, and these weights are the **values** that are learned during the **training** operation. In general, the learning operation comprises target data input to the output nodes 188, which are utilized

for a compare operation and then a **training** algorithm, such as a back propagation technique is utilized, as illustrated by block 192. This...

...will be described hereinbelow, this network is trained through any one of a number of **training** algorithms and architectures such as **Radial Basis Functions** , Gaussian Bars, or conventional Backpropagation techniques. The Backpropagation learning technique is generally described in D...

...which document is incorporated herein by reference. In this type of algorithm, a set of **training** data is input to the input layer 186 to generate an output, which output in...

...error back propagated from the output layer 188 to the input layer 186 with the **values** of the weights on the input interconnect layer and the output interconnect layer changed in accordance with the gradient descent technique. Initially, the error is very large, but as **training** data is sequentially applied to the input, and this compared to corresponding target output data...

...FIGURE 17, there is illustrated a flowchart illustrating the determination of time delays for the **training** operation. This flowchart is initiated at a block 198 and then flows to a function...

...to FIGURE 13. The program then flows to a decision block 202 to determine whether **variable** (tau)s are to be selected. The program flows along a "Y" path to a function block 204 to receive an external input and vary the **value** of (tau) in accordance with the relationship selected by the operator, this being a manual operation in the **training** mode. The program then flows to a decision block 206 to determine whether the **value** of (tau) is to be learned by an adaptive **algorithm** . If **variable** (tau)s are not to be selected in ...program then flows around the function block 204 along the "N" path thereof.

If the **value** of (tau) is to be learned adaptively, the program flows from the decision block 206 to a function block 208 to learn the **value** of (tau) adaptively. The program then flows to a function block 210 to save the **value** of (tau). If no adaptive learning is required, the program flows from the decision block 206 along the "N" path to function block 210. After the (tau) **parameters** have been determined, the model 20 is trained, as indicated by a function block 212 and then the **parameters** stored, as indicated by a function block 214 and then the program flows to a...

...block 236.

Function block 236 flows to a decision block 238 to determine whether the **value** of (tau) is to be varied. If so, the program flows to a function block 240 to set the **value** of (tau) **variably** , then to the input of a function block 242 and, if not, the program flows...

...run time inputs and then flows to a function block 244 to load the model **parameters** . The program then flows to a function block 246 to process the generated inputs through...

...now to FIGURE 19, there is illustrated a flowchart for the operation of setting the **value** of (tau) **variably** . The program is initiated at a block 252 and then proceeds to a function block 254 to receive the external control input. The **value** of (tau) is varied in accordance with

the relationship stored in the storage area 14...

...The data is then preprocessed in the preprocess block 34 in accordance with the preprocess **parameters** stored in the storage area 14. The data is then delayed in the delay block...
...this delay block 18 also receiving the external block control input, which is comprised of **parameters** on which the **value** of (tau) depends to provide the **variable** setting operation that was utilized during the **training** mode. The output of the delay block is then input to a selection block 260...

...a control model 264 is provided. Both models 262 and 264 are identical to the **training** model 20 and utilize the same **parameters** ; that is, models 262 and 264 have stored therein a representation of the system that was trained in the **training** model 20. The predictive system model 262 provides on the output thereof a predictive output...

...has been provided a predictive network for operating in a runtime mode and in a **training** mode with a data preprocessor for preprocessing the data prior to input to a system...

...mapping the input layer to the output layer through a representation of a runtime system. **Training** data derived from the **training** system is stored in a data file, which **training** data is preprocessed by a data preprocessor to generate preprocessed **training** data. which is then input to the non-linear network and trained in accordance with a **predetermined** **training** **algorithm** . The model **parameters** of the non-linear network are then stored in a storage device for use by...

...runtime data is preprocessed by the data preprocessor in accordance with the stored data preprocessing **parameters** input during the **training** mode and then this preprocessed data input to the non-linear ...in a prediction mode. In the prediction mode, the non-linear network outputs a prediction **value** .
Although the preferred embodiment has been described in detail, it should be understood that various...

CLAIMS 1. A predictive network, comprising:
a data storage device for storing **training** data from a runtime system (24);
a data preprocessor (34') for preprocessing received data in accordance with **predetermined** preprocessing **parameters** to output preprocessed data;
a system model (26') having an input for receiving said output...

...an output through a stored representation of said runtime system in accordance with associated model **parameters** (22) that define said stored representation;
a **control device** (37) for controlling said data preprocessor (34') in a **training** mode to preprocess said stored **training** data and output preprocessed **training** data and, in a runtime mode, to receive and preprocess runtime data received from said runtime system to output preprocessed runtime data;
a **training** device operating in said **training** mode to train said system model (26') with said stored **training** data in accordance with a **predetermined** **training** **algorithm** to define said model

parameters (22); and
said system model (26') operating in said runtime mode to generate a predicted...

...2. The network of Claim 1, and further comprising:
an input device for determining said **predetermined** preprocessing **parameters** in accordance with **predetermined** criteria;
a **parameter** storage device for storing said determined preprocessing **parameters** after determination by said input device; and
said data preprocessor controlled by said **control device** to select said determined preprocessing **parameters** from said **parameter** storage device in said runtime mode and to operate under the control of said input device during said **training** mode.
3. The network of Claim 1, wherein said data preprocessor comprises:
an input buffer...

...to be preprocessed being on different time scales;
a time merge device for selecting a **predetermined** time scale and reconciling the data stored in said input buffer such that all of...

...network of Claim 3, and further comprising a pre-time merge processor for applying a **predetermined** algorithm to the data to be preprocessed received by said input buffer prior to input...
...3, wherein said output device further comprises a post-time merge processor for applying a **predetermining** algorithm to the data reconciled by said time merge device prior to output as said...

...select portions of said data to be preprocessed from said input buffer and introducing a **predetermined** amount of delay therein to output delayed data; and
an output device for outputting the...

...7. The data preprocessor of Claim 6, wherein said received data comprises a plurality of **variables** , each of the **variables** comprising an input **variable** with an associated set of data, wherein said delay device is operable to receive at least a select one of said input **variables** and introduce said **predetermined** amount of delay therein to output a delayed input **variable** and an associated set of output delayed data having the associated delay.
8. The data...

...delay.
9. The network of Claim 1, wherein said system model is a non-linear **neural network** with an input layer for receiving said runtime data and providing a predicted output on...
...input layer to said output layer through said stored representation of said runtime system, said **neural network** operable in said **training** mode to receive said stored **training** data on said input and output layers and define said model **parameters** in accordance with said **predetermined training algorithm** .
10. The network of Claim 1, wherein said runtime system is a distributed control system...

...inputs to said system.
11. A predictive network, comprising:
a data storage device for storing **training** data for a runtime system;
a **training** preprocessor (12) for preprocessing said **training** data in

accordance with **predetermined** preprocessing **parameters** to output preprocessed **training** data;

a first memory (14) for storing said preprocessing **parameters** ;

a **training** network (20) having model **parameters** associated therewith for receiving said preprocessed **training** data and adjusting said model **parameters** in accordance with a **predetermined** **training** **algorithm** to generate a representation of said runtime system;

a second memory (22) for storing said adjusted model **parameters** associated with said generated system representation;

a runtime preprocessor (34) similar to said **training** preprocessor for receiving runtime data from said runtime system and preprocessing said runtime data in accordance with said stored preprocessing **parameters** in said first memory to output said preprocessed runtime data; and

a runtime network (26) similar to said **training** network for generating a representation of said runtime system in accordance with said stored model **parameters** in said second memory and for receiving said preprocessed runtime data and generating a predicted output.

12. The network of Claim 11, wherein said runtime preprocessor operates in **real** time.

13. The network of Claim 11, wherein each of said **training** and runtime data preprocessors comprise:

an input buffer for receiving and storing data to be...

...the received data being on different time scales;

a time merge device for selecting a **predetermined** time scale and reconciling the received data stored in said input buffer such that all...

...by said time merge device as said preprocessed data to the respective one of said **training** network or said runtime network.

14. The network of Claim 11 wherein each of said **training** and runtime data ...for receiving select portions of said received data from said input buffer and introducing a **predetermined** amount of delay therein to output delayed data; and

an output device for outputting the...

...A method for generating a prediction in a predictive network, comprising the steps of:

storing **training** data received from a runtime system (24) in a data storage device;

providing a data preprocessor (34') that is operable to preprocess received data in accordance with **predetermined** preprocessing **parameters** to output preprocessed data;

providing a system model (26') that is operable to map input...

...output layer through a stored representation of the runtime system in accordance with associated model **parameters** (22') that define the stored representation;

operating the data preprocessor (34') in a **training** mode to receive the **training** data from the data storage device and output preprocessed **training** data;

training the system model on the preprocessed **training** data to define the model **parameters** (22');

storing the trained model **parameters** generated in the **step** of **training** ;

operating the data preprocessor (34') in a runtime mode to receive

runtime data and generate preprocessed runtime data; and

operating the system model (26') with the trained system model **parameters** to receive on the input thereof the preprocessed runtime data and generate a predicted output on the output thereof.

16. The method of Claim 15, and further comprising the **steps** of:

determining the **predetermined** preprocessing **parameters** in accordance with **predetermined** criteria;

storing the determined preprocessing **parameters** after determination thereof; and

selecting the stored determined preprocessing **parameters** in the runtime mode for the operation of the data preprocessor and determining the **predetermined** preprocessing **parameters** during the **training** mode.

17. The method of Claim 15, wherein the step of operating the data preprocessor in both the runtime mode and the **training** mode comprises:

receiving and storing the data to be preprocessed, the data to be preprocessed being on different time scales;

selecting a **predetermined** time scale and time merging the data stored in the input buffer such that all...

...wherein the step of operating the data preprocessor in both the runtime mode and the **training** mode comprises:

receiving and storing data to be preprocessed;

selecting portions of the stored data to be preprocessed and introducing a **predetermined** amount of delay therein to output delay data; and

outputting the undelayed and delayed portions...

39/3,K/29 (Item 29 from file: 348)
DIALOG(R)File 348:EUROPEAN PATENTS

00916907
MODEL-BASED FAULT DETECTION SYSTEM FOR ELECTRIC MOTORS
MODELLGESTUTZTES FEHLERDETEKTIONSSYSTEM FUR ELEKTROMOTOREN
SYSTEME DE DETECTION DE PANNES A L'AIDE D'UN MODELE POUR MOTEURS ELECTRIQUES

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LANGUAGE (Publication,Procedural,Application): English; English; English
FULLTEXT AVAILABILITY:

Available Text	Language	Update	Word Count
CLAIMS B	(English)	200508	1832
CLAIMS B	(German)	200508	1664
CLAIMS B	(French)	200508	2007
SPEC B	(English)	200508	6916
Total word count - document A			0
Total word count - document B			12419
Total word count - documents A + B			12419

...SPECIFICATION as sound, temperature, voltage and others from corresponding sensors are received and evaluated using a **neural network** by means of **fuzzy logic** and are used to control the engine or motor and for diagnosing and localising faults...

...priori information about all possible faults and the effect each such fault has on the **residuals** .
Accordingly, a period of **time** is required to **monitor** defective and normal **equipment** and to develop a data base which contains fault signatures for fault classification purposes. This...system 30 is able to classify and display the mechanical basis for the fault or **degradation** in motor performance as shown at **step** 82. Model 44 replaces the need to

develop a priori information about the motor.
The...

...motor, the repairman selects the base motor model of the motor being tested and performs **fault** detection and **diagnostic** .

The method and **apparatus** can also be used for condition **monitoring** and **predictive** maintenance applications. In this embodiment, the third embodiment, the MQM algorithm replaces the MCM algorithm...

39/3,K/20 (Item 20 from file: 348)
DIALOG(R)File 348:EUROPEAN PATENTS

01288754
Method and apparatus **for optimizing a control system for a unit device integrated in a** machine **assembly**
Verfahren und Gerat zur Optimierung eines Steuerungssystems fur eine in einem Maschinenaggregat integriert Einheit
Procede et appareil pour l'optimisation d'un systeme de commande pour une di-unite integree a un ensemble de machine
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Method and apparatus **for optimizing a control system for a unit device integrated in a** machine **assembly**
... **optimisation d'un systeme de commande pour une di-unite integree a un ensemble de** machine

...ABSTRACT A2
The invention provides an optimization device for a unitary apparatus that can obtain optimum **characteristics** as a combined apparatus,

without losing user's selectivity and unitary apparatus's versatility. The optimization device includes an optimization process section that in **real** time optimizes dynamic **characteristics** of the unitary **apparatus** , with functional **characteristics** of a combined apparatus as evaluation reference.

...SPECIFICATION of the Invention

The invention relates to an optimization method and device for optimizing dynamic **characteristics** of a unit device (unitary apparatus) integrated in a machine assembly (combined apparatus) that comprises...

...that are used as complete products by combining a plurality of apparatuses (called the "combined **apparatuses** " hereunder). Many combined **apparatuses** are controlled by **control devices** , where dynamic **characteristics** of at least one unitary **apparatus** are appropriate. The **examples** for this case are a motor boat used by combining an outboard motor and a...

...and an air conditioner used by combining an outdoor machine and an indoor machine.

The **characteristics** of a control module for a unitary apparatus (that is, **parameter values** that determine the relationship between input and output of the control module) used for combined apparatuses are decided by combining apparatuses. When **characteristics** of combined apparatuses and use environment can be found beforehand, the **characteristics** of control modules are designed adjustably with respect to combining apparatuses so that they can...

...apparatuses that can be combined, or when combined apparatuses are used in changing environment, the **characteristics** of control modules are determined, supposing the apparatuses to be combined and the environment, in order that they can be met as much as possible.

Moreover, there are proposed a **fuzzy inference** for optimizing **characteristics** of a fuzzy controller in response to fluctuations of supposed use environment and user's **characteristics** , and a method of optimizing **characteristics** of a fuzzy controller in **real** time by using a **neural network** or heuristic rule.

Summary of the Invention

However, when the **characteristics** of a control module for a unitary apparatus used for combined apparatuses are determined in...

...apparatus, and that there is no versatility with a unitary apparatus itself. Even if the **characteristics** of a control module for a unitary apparatus can be adjusted, when the adjustable range...

...to specific apparatuses, versatility is lost and user's selectivity is lost, too.

When the **characteristics** of a control module is decided, supposing the apparatuses to be combined and use environment...

...provide an optimization device of a unitary apparatus for combined apparatuses that can obtain optimum **characteristics** , without losing user's selectivity and versatility of a unitary apparatus.

One aspect of the invention is directed to an optimization apparatus for optimizing an operation **characteristic** of a unitary apparatus that can be used as a combined **apparatus** by combining other **apparatuses** .

The optimization **apparatus** comprises an optimization process device for, in real **time** , optimizing the **operation** characteristic of the unitary **apparatus** , with a functional characteristic of the combined **apparatus** as an **evaluation** criterion.

Preferably, the optimization **apparatus** further comprises a basic control module for deciding a manipulated **variable** of the unitary **apparatus** based on **predetermined** input information, whereby the optimization process device optimizes control **parameters** of the basic control module with a control **characteristic** of the combined apparatus as an evaluation criterion.

Advantageously, in **addition** to the above, the optimization apparatus further comprises a compensation control module for deciding compensation quantity or compensation ratio of the manipulated **variable** based on **predetermined** input information, whereby the optimization process device optimizes control **parameters** of the compensation control module with the control **characteristic** of the combined **apparatus** as an **evaluation** criterion.

Another aspect of the present invention is a method for optimizing in **real - time** **operation** of a **machine** assembly manipulated by a user, said machine assembly comprising plural replaceable devices, each device being...

...a control module, the input-output relationship of which control module is regulated by control **parameters** , said method comprising the **steps** of: (a) operating the replaceable devices using control modules; (b) optimizing in **real** -time the input-output relationship of at least one control module by coding into templates **parameters** fully or partially regulating the control module, said templates being subjected to heuristic processing, wherein at least one fitted set of **parameters** is selected by evaluating output of the machine assembly based on the user's ultimate...

...advantages may be achieved in accordance with any particular embodiment of the invention. Thus, for **example** , those skilled in the art will recognize that the invention may be embodied or carried...of the present invention.

Figure 1e is a schematic diagram illustrating one embodiment of a **fuzzy** **inference** control module.

Figure 2 is a block diagram illustrating one embodiment of an optimization device...

...a combined apparatus in accordance with the invention.

Figure 3 is a figure illustrating a **control** **device** and an outboard motor including a trimming **apparatus** .

Figure 4 is a block diagram illustrating an inner structure of a **control** **device** .

Figure 5 is a block diagram illustrating an inner structure of a **control** **device** .

Figure 6 illustrates relationship between standardized **coefficients** of a boat operation fuzzy control module and individuals produced by encoding them.

Figure 7...

...evolutionary process by a constant-speed navigationcontrol unit.

Figure 9 is a graph illustrating one **example** of performing time division when a plurality of individuals is evaluated by time-division.

Figure 10 illustrates one **example** of an interface for switching between regular control mode and evolutionary mode.

Figure 11 illustrates one **example** of seeking a total of fitness of fuzzy rules.

Figure 12 is a graph showing the relationship between boat speed-resistance curve and trim positions.

Figure 13 shows one **example** of individuals used in an autonomous evolutionary process unit in an acceleration optimization control section ...

...a machine assembly.

An aspect of the present invention is a method for optimizing in **real** -time operation of a **machine** assembly manipulated by a user. The machine assembly comprises plural replaceable devices, each device being ...

...a control module. The input-output relationship of the control module is regulated by control **parameters** . Figure 1a is a schematic diagram illustrating one embodiment of the optimization system. In this...

...are conducted: (a) operating replaceable devices (devices #1, #2) using control modules; (b) optimizing in **real** -time the input-output relationship of at least one control module (the control module for device #1) by coding into templates **parameters** (a1, a2, a3,...) fully or partially regulating the control module, said templates being subjected to heuristic processing, wherein at least one fitted set of **parameters** is selected by evaluating output of the machine assembly based on the user's ultimate...

...evolutionary computation, and the templates are chromosomes.

When controlling complex devices or unstandarized devices, a **fuzzy inference** system is useful. Figure 1 e is a schematic diagram illustrating one embodiment of a **fuzzy inference** control module, wherein the control module regulated by control **parameters** is provided with a **fuzzy inference** system comprising a matrix of fuzzy rules which are regulated by preselected **parameters** , and the optimization **step** is conducted by at least one of the following: (i) revising the fuzzy rule matrix...

...the membership functions into chromosomes; or (iii) changing a level of an input of the **parameters** and a level of an output of the **fuzzy inference** system by coding elements of the levels into chromosomes.

In the above, the method may...

...in (ii) or the membership functions to be modified in (iii).

In the above, the **parameters** may be (i) the number, shape, position and/or expanse of membership functions for the **fuzzy inference** system of the **control device** , (ii) fuzzy rules, or (iii) standardized **coefficients** for input and output **values** . The fuzzy rules can be compiled in the form of a fuzzy rule ...by membership functions. Each section of the matrix represents a fuzzy rule which is a **parameter** having a **value** . The type of **parameter** and a **value** of the **parameter** are referred to as "a **parameter** ".

Coding into chromosomes or templates can be made on all of the **parameters** or part thereof selected for the fuzzy controller.

In the present invention, correlations between various inputs and various outputs of the control modules can be determined using **existing** techniques such as **neural networks** , fuzzy **neural networks** , and genetic algorithms if the correlations are highly complex, or using **existing** techniques such as maps and functional equations if the

correlations are rather simple. In this regard, Da Ruan (editor)"Intelligent Hybrid Systems -- **Fuzzy Logic** , **Neural Networks** , and Genetic Algorithms--" Kluwer Academic Publishers (1997), J.-S. R. Jang, C.-T. Sun, E...

...Systems" Prentice Hall Upper Saddle River, NJ 07458 (1998), and N. K. Kasabov, "Foundations of **Neural Networks** , Fuzzy Systems, and Knowledge Engineering" the MIT Press (1996) are hereby incorporated by reference. The...

...al. (editor), "Genetic Programming, An Introduction", pp.363-377, 1999, Morgan Kaufmann Publishers, Inc., for **example**). These techniques are sometimes categorized as "heuristic control" which includes evolution, **simulated** annealing, and reinforcement learning method (S. Suzuki, et al., "Vision-Based Learning for **Real** Robot: Towards RoboCup", RoboCup - 97 Workshop, 23, 24, and 29 August, 1997 Nagoya Congress Center, pp. 107-110; K. and Nurmela, et al., "Constructing Covering Designs By **Simulated** Annealing", pp. 4-7, Helsinki University of Technology, Digital Systems Laboratory, Technical Reports No. 10, January 1993, for **example**). These techniques can be adapted to the present invention without complication, based on the principle...

...207 that, based on the input information, decides and outputs information related to a manipulated **variable** , compensated amount, or manipulated **variable** for a compensation **coefficient** , toward a unitary apparatus 209 constituting a combined apparatus 208 together with another apparatus 210. The control module 207 is, preferably, the one that employs a **fuzzy inference** system, for **example** , a fuzzy controller, fuzzy intention determination system, or fuzzy neurocontroller. But, the control module 207...

...204 and an autonomous evolutionary process unit 205. These process units 204 and 205 optimize **parameters** of the control module 207 during use of the combined **apparatus** 208, i.e., in **real** time, using **characteristics** of the combined **apparatus** 208 as evaluation reference.

The **parameters** to be optimized can be any type of **parameter** as long as they are related to the control module. For **example** , when a **fuzzy inference** system is employed, cited as such are the **parameters** for deciding the number, shape, position and expanse of a membership function, the fuzzy rules, and the standardized **coefficients** for input and output **values** . With regard to evaluation for optimization, the interactive evolutionary process unit 204 receives evaluation **values** applied by the user 202, and the autonomous evolutionary process unit 205 accepts evaluation **values** from the evaluation unit 206 which is designed beforehand based on **predetermined** evaluation criteria.

By, in **real** time, optimizing **parameters** of the control module that controls the unitary apparatus, using **characteristics** of the combined apparatus as evaluation reference, the unitary apparatus can be optimized to fit...

...and a trimming apparatus for a planing boat.

Figure 3 is a figure illustrating a **control device** and an outboard motor including a trimming **apparatus** . An outboard motor 32 is mounted to a hull 31. The outboard motor 32 includes...

...cylinder 36 and a hydraulic pump 37. The outboard motor 32 is connected

to an **control device** 30.

The **control device** 30 optimizes boat operation **characteristics** and acceleration **characteristics** which realize a constant speed navigation control and acceleration optimization control in response to changes in the movement of the hull 31 and disturbances. The **control device** 30 also optimizes the boat operation **characteristics** and acceleration **characteristics** , by responding to preferences of users-when the users are different, or when the preferences of even one and the same user vary dependent on time, for **example** , when his preferences vary in spring or fall. The "boat operation **characteristics** " herein mean boat speed control **characteristics** by the operations of the electronic throttle valve 34 and the trimming **apparatus** 35.

The **control device** 30 inputs the **engine** speed, the speed, acceleration, steering angle, and throttle opening of the hull 31, and the evaluation **value** . The **control device** 30 outputs an electronic throttle valve opening variation and a trim angle variation to operate...

...acceleration optimization control.

Figure 4 is a block diagram illustrating an inner structure of a **control device** 400. The **control device** 400 includes a constant speed navigation control section 403, and an acceleration optimization control unit...

...boat operation fuzzy control module 407, an autonomous evolutionary process unit 405, a boat-operation **characteristic** evaluation unit 406, and an interactive evolutionary process unit 404. The boat operation fuzzy control...

...electronic throttle valve for an electronic throttle 410 and a trim angle for a trimming **apparatus** 411 in response to **predetermined** input information. The autonomous evolutionary process unit 405 optimizes standardized **coefficients** of the boat operation fuzzy control module 407. The boat-operation **characteristic** evaluation unit 406 evaluates the autonomous evolutionary process unit 405. The interactive evolutionary process unit...

...control module 407.

Figure 5 is a block diagram illustrating an inner structure of a **control device** 500. An acceleration optimization control unit 504 includes a trim control module 508, an autonomous evolutionary process unit 506, an acceleration **characteristic** evaluation unit 507, and an interactive evolutionary process unit 505. The trim control module 508 determines a trim angle for a trim **apparatus** 511 in response to **predetermined** input information. The autonomous evolutionary process unit 506 optimizes control **parameters** of the trim control module 508. The acceleration **characteristic** evaluation unit 507 evaluates the autonomous evolutionary process unit 506. The interactive evolutionary process unit 505 optimizes control **parameters** of the trim control module 508.

The "standardized **coefficients** " mean **coefficients** that adjust amount of input and output information.

1. Control by a Constant Speed Navigation Control Unit

The boat operation fuzzy control module employs a simplified inference method as a **fuzzy inference** system, and outputs an electronic throttle valve opening variation and a trim angle variation in...

...based on the boat operation knowledge of the skilled. The fuzzy rule is expressed by **real** number **values** .

Figure 6 illustrates relationship between standardized **coefficients** of a boat operation fuzzy control module 60 and individuals produced by encoding them. The speed is applied to standard **coefficient** S1; the acceleration, S2; the throttle opening, S3; the steering angle, S4; and the engine...

...information is applied to the boat operation fuzzy control module 60 through its corresponding standard **coefficient** . The boat-operation fuzzy control module 60 outputs the electronic throttle valve opening variation and the trim angle variation through the corresponding standard **coefficient** S6 and S7, respectively. The autonomous evolutionary process unit in the constant speed navigation control unit uses a genetic **algorithm** , and encodes the standardized **coefficients** of the boat operation fuzzy control module 60 as shown in Figure 6 to produce individuals. The autonomous evolutionary process unit optimizes the standardized **coefficients** by using the genetic **algorithm** . With regard to evaluation of each individual during autonomous evolutionary process, regarding boat operating **characteristics** , higher evaluation **values** are provided by the evaluation unit as an error between an **actual** speed and a reference a user has fixed gets closer to a **desired** range. As a result, the standardized **coefficients** of the boat operation fuzzy control module 60 are automatically optimized towards the **desired** boat operating **characteristics** , and an optimal boat operating **characteristic** is obtained even when the use environment changes or the hull moves inappropriately.

Thus, the...

...is optimized based on the evaluation of the user to produce an optimal boat operating **characteristic** suitable for the user's evaluation.

The method the user employs regarding the evaluation in...

...a. Evolutionary Process in an Autonomous Evolutionary Process Unit

As shown in Figure 8, initial **values** of the standardized **coefficients** are determined at random within a range decided beforehand to produce first generation comprising a...

...explained here. A plurality of individuals is operated in parallel by time division and evaluation **values** are compared by a total of the duration. To be specific, evaluation is changed according to a range of **engine** speed used.

Figure 9 is a graph illustrating one **example** of performing time division when a plurality of individuals is evaluated by time-division. As...

...low speed of an engine is used, ten individuals are controlled every minute, and absolute **values** of the difference between a reference and an **actual** speed are totaled every sampling time. Making this one cycle, twenty cycles are repeated to calculate a total within an evaluation period as an evaluation **value** . By doing so, since influence by disturbances such as atmospheric phenomena and oceanic phenomena (for **example** , wind, or wave) is understood as a total through the individuals, a fair evaluation of **characteristics** of each individual can be made.

In the case of cruising where a high speed...

...a hull in leftward or rightward. When pitching or Dutch roll is

detected, zero is **given** as an individual evaluation **value** and a trim angle is reduced till pitching or Dutch roll is prevented from producing ...

...which can prevent unstable movements from generating at a high speed.

Based on the evaluation **value** of each individual derived by the evaluation **value** calculation process (**step** 1-2), it is evaluated whether the evaluation **value** is an optimal boat operation **characteristic** (**step** 1-3). As a result of the evaluation, it is decided whether an optimal boat operation **characteristic** is obtained (**step** 1-4). If the optimal boat operation **characteristic** is obtained, the evolutionary process is finished. If not, the process proceeds to an evolutionary...

...1-5).

b. Evolutionary Process in an Interactive Evolutionary Process Unit

Figure 10 illustrates one **example** of an interface for switching between regular control mode and evolutionary mode. As shown in...

...mode and the evolutionary mode is made in accordance with the conditions fixed beforehand, for **example** , time or user's intention through an interface shown in Figure 10.

Figure 11 illustrates one **example** of seeking a total of fitness of fuzzy rules. The regular control mode performs fuzzy...

...following a normal distribution to produce a first generation comprising a plurality of initial individuals (**step** 2-5). A trial ride is made using **parameters** for any individual in the first generation (**step** 2-6). The user inputs an evaluation **value** for the individual (**step** 2-7).

Based on the evaluation **value** , it is decided whether a **desired** boat operation **characteristic** is obtained (**step** 2-8). If it is, the individual is regarded as best and the evolutionary process...

...reached (step 2-11). If it is judged so, the individual with the highest evaluation **value** in the generation is considered to be best and the evolutionary process is ended. If...

...an evaluation using the fuzzy rules for the individuals.

The above process, by which the **desired** boat operation **characteristics** are obtained, is repeated till the number of stipulated generations is reached. As a result...

...used.

2. Control in Acceleration Optimization Control Section

The trim control module outputs a trim **variable** with respect to speed.

Figure 12 is a graph showing the relationship between boat speed- ... kinds of hulls and disturbances, and requires an advanced operation technique.

Figure 13 shows one **example** of individuals used in an autonomous evolutionary process unit in an acceleration optimization control section. In the figure, control **parameters** for a trim control module-trim out initial speed T1, trim operation speed T2, and final trim angle T3-are shown. The autonomous evolutionary process unit employs a genetic **algorithm** . The control **parameters** are encoded to produce

individuals and are optimized using the genetic algorithm. Evaluation of each individual during the autonomous evolutionary process is conducted by an evaluation unit, where an evaluation **value** is higher as a **desired** acceleration **characteristic** , for **example** , time from stop of a boat to a **predetermined** speed becomes shorter. Accordingly, the control **parameters** of the trim control module are automatically optimized to the **desired** acceleration **characteristic** . Even when a use environment or a hull changes, an optimum acceleration **characteristic** can be obtained.

The interactive evolutionary process unit in the acceleration optimization control section employs a genetic **algorithm** . Control **parameters** for a trim control module are coded to produce individuals and are optimized using the...

...process is conducted based on comfortableness a user really feels. As a result, the control **parameters** are optimized in accordance with the user's evaluation and an optimum acceleration **characteristic** that meets user's evaluation can be obtained.

Switching over between the autonomous evolutionary process...

...To be specific, The autonomous evolutionary process unit performs evolutionary process where an optimum acceleration **characteristic** is produced. Based on the optimum acceleration **characteristic** , the interactive evolutionary process unit conducts interactive evolutionary process and a fine adjustment may be...

...like is produced during the autonomous evolutionary process, the user may give a zero evaluation **value** at the scene to change to the next individual.

Next, the evolutionary process in the...

...a. Evolutionary Process in an Autonomous Evolutionary Process Unit

As shown in Figure 14, initial **values** of the control **parameters** are first decided at random within a **predetermined** range to produce a first generation from a plurality of initial individuals (step 1-1...

...accelerated fully open, one time per one individual, from stop of a boat to a **predetermined** speed. Time needed to reach the **predetermined** speed is calculated as an evaluation **value** .

Based on the evaluation **value** for each individual derived from the evaluation **value** calculation process (**step** 1-2), it is evaluated whether it is an optimal acceleration **characteristic** (**step** 1-3). As a result of the evaluation, it is determined whether an optimal acceleration **characteristic** is obtained (**step** 1-4). If an optimal boat operation **characteristic** is obtained, the evolutionary process is finished. If not, an evolutionary calculation module begins to...

...b. Evolutionary Process in an Interactive Evolutionary Process Unit

As shown in Figure 14, initial **values** of the control **parameters** are first decided at random within a **predetermined** range to produce a first generation from a plurality of initial individuals (step 2-1). A trial ride is made by using **parameters** for any one of individual **parameters** in a first generation (**step** 2-2). A user inputs evaluation **values** on the individual (**step** 2-3). Based on the evaluation **values** , it is decided whether a **desired** acceleration **characteristic** is obtained (**step** 2-4). If it is, the evolutionary process is finished. If it is not, it...

...whether a trial ride and evaluation on all the individuals of one generation are over (**step** 2-5). If it is not, the **parameters** for the trim control module are changed to those for another individual (step 2-6 again, another trial ride and evaluation using **parameters** of the individuals are conducted.

The process is repeated till a **desired** acceleration **characteristic** is obtained, and as a result the **parameters** of the trim control module are optimized.

An evaluation of acceleration **characteristics** , which uses an interactive type, is explained here. After acceleration is increased from a stop of a boat to a **predetermined** speed with a throttle fully open, one time per individual, an evaluation **value** is input based on the acceleration and comfortableness a user feels.

Now, some of evolutionary...

...flowchart illustrating an evolutionary computation module when a generic algorithm is used as an evolutionary **computation** method. In the module, when a **desired** **characteristic** is not obtained after completion of an evaluation of all the individuals to one generation...

...as much as possible by replacing the individual with another selected individual.

As for mutation (**step** 4), **values** are changed at random with a constant probability about each locus for individuals. There is...

...next generation, after completing an evaluation of all the individuals to one generation, when a **desired** **characteristic** is not obtained.

As for selection (**step** 1), two exemplary kinds of methods are explained since methods of selection are different owing...

...ES: Adjacent search method

. ((square) + 1)-ES: Successive generation multi-point search method

Regarding crossover (**step** 2), the normal distribution is used. Parents' **values** can be succeeded for each **parameter** , and child's **values** can be a middle point, interpolated point or extrapolated point.

With respect to mutation (**step** 3), perturbation having a normal distribution is added to each **parameter** . The dispersion of the normal distribution may be adjusted every **parameter** or may have interrelationship between the **parameters** .

Since the evolutionary strategy (ES), as explained above, uses each **parameter** as a **real** number, it has the advantage that a transformation from phenotype to genotype is no longer necessary. Using a method of crossover having continuity of **real** numbers such as normal distribution crossover enables parents' character to be reflected more heavily to...

...stochastic, the selection is substantially stochastic.

Since the evolutionary programming (EP) mentioned above uses each **parameter** as a **real** number, it has the advantage that a transformation from phenotype to genotype is no longer necessary. As no crossover is used, there is no limitation in phenotype. The **parameters** of the genetic **algorithm** do not have to be in a string as in the evolutionary strategy, and may...

...The preference of users varies significantly. Therefore, it is impossible to acquire boat speed control **characteristics** that can satisfy all users under every use environment, ...control for the hull are indispensable so as to achieve optimal boat speed control, in

addition to the **characteristics** of use environment and a user. When a fuzzy controller is used as a **control device**, it is difficult to optimize the **characteristics** of the fuzzy controller to fit all conditions. However, as described above, the **parameters** for the boat operation fuzzy control module, which controls an electronic throttle valve and a trim, may be optimized in **real** time by using the evolutionary calculation. Accordingly, the invention has the distinct advantage that the...

...realize constant speed navigation control. The constant speed navigation control unit determines, based on the **predetermined** input information, an opening of the electronic throttle valve and a trim angle through a boat operation fuzzy control module. The standardized **coefficients** for the boat operation fuzzy control module are optimized using an autonomous evaluation, and the...

...the acceleration control. The acceleration optimization control unit determines the trim angle based on the **predetermined** input information through the trim control module. The control **parameters** for the trim control module are optimized using the autonomous and interactive evaluations. These are...

...apparatus in accordance with the invention is not limited to the embodiments mentioned above. For **example**, the evaluation may be made based on fuel consumption rate and/or power rate, or...

...comprises an engine, a water nozzle apparatus, and a hull. The engine and water nozzle **apparatus** constitute a unitary **apparatus**. When the invention is applied, a **control device** that controls an electronic throttle and a water nozzle trim **apparatus** in the engine are optimized with the **characteristics** of the personal water craft as an evaluation criterion. The control of the intake of...

...having a gasoline engine. When the invention is applied with the outboard motor and trim **apparatus** as a unitary **apparatus**, the **control device** that controls an electronic throttle valve **apparatus** and a trim **apparatus** in the engine can be optimized with the **characteristics** of the planing boat as an evaluation criterion. Then control of intake of air and...

...movable apparatus. When the invention is provided by treating the outboard motor and flap movable **apparatus** as a unitary **apparatus**, the **control device**, which controls a fuel injection **apparatus** in the **engine** and the flap movable apparatus, are optimized with the **characteristics** of the planing boat a evaluation criterion. Then the control of quantity of fuel injection...

...is not limited to the embodiment described above. Instead, the controlled system may be any **control device** so long as the **control device** controls an operation **characteristic** of unitary **apparatuses** that are used as a combined **apparatus** by combining other **apparatuses**. For **example**, the controlled systems shown in Figures 21-23 are candidates.

Figure 21 shows an embodiment where the optimization method in accordance with the invention is applied to a **control device** that controls the movement of a robot. In the embodiment, the **control device** 212 inputs information from an infrared sensor attached to the robot 211, an image input...

...a camera, a voice input device such as a microphone, and an accelerator sensor. The **control device** 212 includes a fuzzy control module (not shown) which outputs information on the movement for the robot 211. The fuzzy control module can be optimized in **real** time.

The **parameters** to be optimized may selected arbitrarily. Evaluation for optimization is made directly by a user...

...The input device to which the user will apply evaluation can be provided separately. For **example** , the input device may be constructed to detect the state of the user by the...

...In this way, when the optimization method according to the invention is applied to the **control device** that controls the movement of the robot, the robot can execute optimal movements, according to a change of robot's bodies (for **example** , a change from a human-type robot to a dog-type robot), a change of...interchangeably mounted to a body thereof. The body 222 of the robot 221 contains a **control device** 223 that controls the movement of each part. When the optimization method in accordance with the invention is applied to the **control device** 223, even if the head, arms, and/or legs are interchanged, the **control device** 223 can be optimized so that an optimal movement may be made according to a...

...an embodiment where the optimization method in accordance with the invention is applied to a **control device** 233 of a bicycle 231 with an electrically driven auxiliary power unit 232. The **control device** 233, including a fuzzy control module, receives a stepping force for a pedal from a user, a speed, an acceleration, and an evaluation **value** , and outputs an assist force to the electrically-driven auxiliary power unit 232, decided by the fuzzy control module. The fuzzy control module is optimized in **real** time.

The optimization method in accordance with the invention is applied to the **control device** 233 of the bicycle 231 with the electrically driven auxiliary power unit 232. Even if the bicycle 231 may be interchanged to a new bicycle to which the **control device** 233 is attached, the assist force can be optimized in **real** time for the new bicycle. This reduces the limitations to the kinds of bicycle. Even...

...age or physique of a user, an assist force, or duration of a battery, a **control device** is optimized in **real** time so that an optimal assist force may be generated. As far as an apparatus has an electrically driven auxiliary power unit, the same effect can be obtained from any **apparatus** , for example, a wheelchair.

In the control device for controlling an operation characteristic of the unitary **apparatus** that is used as a combined **apparatus** by combining other **apparatuses** , the optimization process unit is provided for, in real **time** , optimizing an **operation** characteristic of the unitary **apparatus** , with the functional **characteristics** of the combined **apparatus** as an **evaluation** criterion. Accordingly, the invention produces an advantage that without losing user's selectivity and versatility of the unitary apparatus, optimum **characteristics** as the combined apparatus can be obtained.

It will be understood by those of skill...

...invention. Therefore, it should be clearly understood that the forms of the present invention are **illustrative** only and are not intended to limit the scope of the present invention.

...CLAIMS A2

1. A method for optimizing in **real** -time operation of a **machine** assembly manipulated by a user, said machine assembly comprising plural replaceable devices, each device being...

...a control module, the input-output relationship of which control module is regulated by control **parameters** , said method comprising the **steps** of:

(a) operating the replaceable devices using control modules;

(b) optimizing in **real** -time the input-output relationship of at least one control module by coding into templates **parameters** fully or partially regulating the control module, said templates being subjected to heuristic processing, wherein at least one fitted set of **parameters** is selected by evaluating output of the machine assembly based on the user's ultimate...

...chromosomes.

7. The method according to Claim 6, wherein the control module regulated by control **parameters** is provided with a **fuzzy** **inference** system comprising a matrix of fuzzy rules which are regulated by preselected **parameters** , and the optimization **step** is conducted by at least one of the following:

(i) revising the fuzzy rule matrix...

...the membership functions into chromosomes; or

(iii) changing a level of an input of the **parameters** and a level of an output of the **fuzzy** **inference** system by coding elements of the levels into chromosomes.

8. The method according to Claim...

...a trim apparatus and an electronic throttle.

11. An optimization apparatus for optimizing an operation **characteristic** of a unitary apparatus that can be used as a combined **apparatus** by combining other **apparatuses** , the optimization **apparatus** comprising:

an optimization process device for, in real **time** , optimizing the **operation** characteristic of the unitary **apparatus** , with a functional characteristic of the combined **apparatus** as an **evaluation** criterion.

12. The optimization **apparatus** of Claim 11, further comprising a basic control module for deciding a manipulated **variable** of the unitary **apparatus** based on **predetermined** input information, whereby the optimization process device optimizes control **parameters** of the basic control module with a control **characteristic** of the combined apparatus as an evaluation criterion.

13. The optimization apparatus of Claim 11...

...comprising a compensation control module for deciding compensation quantity or compensation ratio of the manipulated **variable** based on **predetermined** input information, whereby the optimization process device optimizes control **parameters** of the compensation control module with the control **characteristic** of the combined apparatus as an evaluation criterion.

14. The optimization apparatus according to at...

...and an autonomous evaluation unit for evaluating with respect to optimization process based on a **predetermined** evaluation criterion, whereby the optimization process device controls using control **parameters** obtained by the optimization operation unit, and evaluating the result at the evaluation unit, carries...

...s intention with respect to optimization process, whereby the optimization process device controls using control **parameters** obtained by the optimization operation unit, and evaluating the result at the evaluation unit based...An optimizer for a unit device for an assembly in a controller for controlling operating **characteristics** of said unit device which is combined with another device to be used as an assembly, wherein it has an optimizing process unit for performing **real** -time optimization of the operating **characteristics** of said unit device using functions of the assembly as criteria for evaluation.

21. An...

...basic control module for determining an amount of operation of said unit device based on **predetermined** input information; and said optimizing process unit optimizes control **parameters** of said basic control module using control **characteristics** of the assembly as criteria for evaluation.

22. An optimizer according to Claim 20 or...

...basic control module for determining an amount of operation of said unit device based on **predetermined** input information and a control module for correction for determining an amount or ratio of correction for the amount of operation based on **predetermined** input information; and said optimizing process unit optimizes control **parameters** of said control module for correction using control **characteristics** of the assembly as criteria for evaluation.

23. An optimizer according to at least one...

...process based on preset criteria for evaluation; and said optimization process unit conducts optimization by **actually** performing control using the control **parameters** obtained by said optimization process unit and evaluating the results with said evaluation unit.

24...

...of the user regarding the optimization process; and said optimization process unit conducts optimization by **actually** performing control using the control **parameters** obtained by said optimization process unit and evaluating the results based on evaluation information input ...

39/3,K/124 (Item 65 from file: 349)
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METHODS **AND** APPARATUS **FOR** MONITORING **AND** **DIAGNOSING** SYSTEM **PERFORMANCE**
PROCEDES ET APPAREIL DE CONTROLE ET DE DIAGNOSTIC DU FONCTIONNEMENT D'UN SYSTEME
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METHODS **AND** APPARATUS **FOR** MONITORING **AND** **DIAGNOSING** SYSTEM **PERFORMANCE**
Fulltext Availability:
Detailed Description
Claims

English Abstract
...which must occur prior to the pre-defined event occurring and one or more critical **parameters** defining the data which must occur during the system's performance for the event to...

Detailed Description
... tasks involved in maintaining such systems also increases. The maintenance tasks include, by way of **example** only, **fault** **diagnosis** , fault location,, performance **monitoring** , performance optimization and repair. These tasks are typically performed by an,expert technician,, by analytical diagnostic **tools** @or by a combination thereof, Many diagnostic tools are known for use in maintenance tasks...

...even where the expert has had sufficient experience with the complex 25 system. See, for **example** ,; "The Thinking **Machine** - An Electronic Clone of a Skilled **Engineer** is Very Hard To Create", in the August 12, 1988 issue of the Wall Street...not put into regular use,
Expert systems based on surface knowledge representations, therefore, require an **exhaustive** set of a priori rules which accurately encompass the spectrum of the possible faults of...
...have also incorporated deep knowledge

representations of systems under test, wherein the
functional and structural **qualities** of a system's components are qualitatively modeled to show connectivity and **behavioral** relationships. This approach enables a diagnostic tool to deal with imprecise **behavioral** and structural **characteristics** of a system, such as dynamic changes in connectivity, which can not be addressed in...

...greater
flexibility in reasoning. Such qualitative models can represent the operation of a system without **exhaustive** a priori enumeration of all possible failure models, as required in surface knowledge approaches,
Diagnostic...

...embodying heuristic rules developed by system maintenance experts and a deep knowledge representation embodying component **behavior** and system connectivity is suggested. It is also suggested to use reliability statistics as an...
...cases such a system is dependent on a heuristic surface knowledge representation and the required **exhaustive** enumeration of a priori rules, which can be difficult to develop, Causal reasoning with a...respond to suspected abnormalities by either
issuing a warning, shutting the system down, or causing **predetermined** data to be recorded in a nonvolatile memory or other recording devices,
The effectiveness of...

...speed'at which the evaluation of the collected system performance data can be made, the **quality** of the evaluation made, the specificity of the abnormality identified, and the **quality** and quantity of the collected performance data stored for future diagnostic of analytical use, Presently...

...performance data quicker and more
completely., control data acquisition for so as to improve the **quality** and quantity of data stored for ...occur prior to the occurrence of the
pre-defined event and with one or more **parameter** conditions which must occur during the performance of the system for the pre-defined event...

...defining the event record are found or if there are no such events, then the **parameter** conditions found in the first event record are compared to the acquired ope-rational data, If a match is found when comparing the **parameter** conditions, then the event defined by the first event record is recognized.

The comparison steps...

...a connected computer system or it may be
embedded in the database model, As an **example** , each event record may include a list of actions to be performed in the

...the recogni.zed events to determine the systems performance can result in modifying a performance **parameter** in the system, modifying the data acquisition system or warning an operator of the system under test; Figure 8 illustrates the comparison of the **actual** results of a test performed on a system under test to the expected results...

...a result of the monitoring system recognizing an event; Figure 16 illustrates a signal being **sampled** by the data acquisition system of the present invention; Figure 17 is a block...

...a preferred embodiment of the present invention, In step 100, a plurality of data **samples** are collected from the system under test during its operation, In step 102, the collected...from any other source are compared to event criteria from the failure model which specify **patterns** that correspond to the rules in the model, Each **pattern** has associated with it a set of ambiguity group effects, as before, In **step** 116, the set of ambiguity group effects corresponding to recognized **patterns** from the failure model are output, In **step** 106, the output set of ambiguity group effects are applied to the ambiguity group, as...and function of the event at location 160 and is represented by a number of **parameters** , These **parameters** include one or more critical **parameters** at location 162 by which the event is recognized, affected **parameters** at location 164 which should be affected by the occurrence of the event, state vector...

...The data 150 collected from the system in step 100 comprises a plurality of data **samples** 170, 172 and 174, This data 150 represents the operational **characteristics** of the system from which the defined events of the event based representation 152-are recognized in step 102, These **samples** are time tagged so that **sample** 170 is associated -with time tl, **sample** 172 is associated with time t2 and so on. Furth-er, calculations can be performed on the collected data 150, and included in the data **samples** 170 to 174 for use in the event recognition process of **step** 102 or the **pattern** recognition process of **step** 114,
The data 150 can be collected by any known data acquisition technique, In a...system having sufficient memory to store the event based representation 152 and the data 150, **real** time event recognition in step 102 is obtainable, A single Acromag acquisition module should be...
...start of diagnostics, the sta-te vector 190 is either empty or loaded with initial **values** .

In **step** 204, the state vector dependencies for the first event record 154 and the state vector...

...the event recognition analysis for event record 154 continues, In step 212, the first data **sample** 170 from the collected data 150 is selected. In **step** 214, the data **sample** 170 is compared to the critical **parameters** found at location 164 is in the event record 154, In step 216, it is determined whether there is a match between the critical **parameters** and the data **sample** , If there is no match, the collected data 150 is examined in step 218 to see if the last data **sample** from collected data 150 was used, If the last data **sample** was used, then step 206 is repeated to see if every event record has been used. If there are more data **samples** , they are retrieved in **step** 220.

If, in **step** 216, a match between the critical **parameters** of event record 154 and the data **sample** 170 is found,, then the event defined by event reco-rd 154 is declared...

...at location 192, Then step 218 is repeated to see if there are more data **samples** to be used, In this way, all data **samples** 170 to 174 from collected data 150 are compared to the critical **parameters** from every event record 154 to 158 from the event based representation 152. Figure 2...

...182 from the set of ambiguity group effects 176 which are to be output from **step** 102, The event record 154 has a plurality of affected **parameters** 230, 232 and 234 at location 164 and a plurality of state vector effects 236 and 238 at location 168. The affected **parameters** 230 to 234 define the states of **parameters** of the system under test which should have been affected in some way by the...

...the event during operation of the system. The --actu-al state of the affected **parameters** can be checked by reference to the collected data 150, The state vector effects 236...

...system, The state vector effects at locations 236 and 238 are related to the affected **parameters** at locations 230 to 236 or to the critical **parameters** at locations-162 either directly of by Boolean operators, Referring to Figure 4, it is seen that state vector effect 238 is directly related to affected **parameter** 230 by pointer 240.

The occurrence of the effect specified by the state vector effect be confirmed by reference back to the event record 154 or other data **samples** as needed and by comparing that data to the components state defined by the affected **parameters** 230. If the component state defined by the affected **parameter** 238 is confirmed. If it is not, then the state vector effect 238 is not confirmed.

Figure 4 also shows state vector effect 236 related to two affected **parameters** 232 and 234 by a Boolean operator 242 through pointers 244, 246 and 248. Any...

...defined if appropriate. The Boolean operator 242 can define any logical combination of affected **parameters** , State vector effect 236 is confirmed, therefore, by referencing data from collected data 150 and comparing it to affected **parameters** 232 and 234 to see if the Boolean operator 242 is satisfied, Each state vector...

...one set for use if the effect is confirmed by reference to the appropriate affected **parameters** and another set for use if the effect is not confirmed by the reference, State...

...is not confirmed, State vector effect 238 is similarly associated with a first set of **parameters** 254 to be used if the effect is4confirmed and a second set of A

parameters 256 to be used'if the effect is not confirmed, The combination of ambiguity group...

...group effects for each recognized event is selected based on the analysis of the affected **parameters** and the state vector effects as described. Referring to Figure 4, assume the effect specified by the state vector effect 236 is.confirmed by reference to affected **parameters** 232 and 234, so that the first set of ambiguity group effects 250 is...

...effect specified by the state vector effect 238 is not confirmed by reference to affected **parameter** 230, so that the second set of **parameters** 256 associated with state vector effect 238 is selected for use with output 182...

...to the recognized events can also be analyzed to select ambiguity group effects, For **example** , if the system under test normally progresses through a sequence of four events but only...If-Then rules, The failure model 320 of the present invention comprises a plurality of **patterns** which are associated with each rule. The failure model 320, therefore, comprises a plurality of **patterns** 324, 326 and 328,
The inputs 330 used for comparison against the **patterns** of the failure model 320 are derived from several sources, Events recognized in step 102...

...Record 332 and 324 also has a pointer that specifies the location of the data **sample** 170 to 174 from which the event was recognized. In this way, the data **samples** 170 to 174 are also available for comparison to the **patterns** of the failure model 320. Similarly, the symptom-fault relationships which were found to exist in **step** 110 are used to form **pattern** recognition records 336 to 338.

The **patterns** 324 to 328 of the failure model 320 are defined by logical combinations of event...

...records 336 to 338, or
to any other inputs 330 which may be applicable, In **step** 114, all of the inputs 330 are compared to each **pattern** 324 to 328 in the failure model 320. The matching required to perform step 114...

...record 332 to 338 can
have many component parts that must be compared to a **pattern** 324 to 328 which may be defined by many event criteria, In the preferred embodiment, CLIPSj
an **artificial** **intelligence**
language, is used to implement a matching algorithm based on the Rate Network, Other languages which can be used include OPS5 and SOAR,
Each **pattern** 324, 326 and 328 in the failure model 320 is associated with a set of ambiguity group effects 340, 342 and 344, respectively, When the matching performed in **step** 114 determines that a **pattern** exists, it is output with its associated set of ambiguity group effects. In Figure 6, for **example** , **pattern** 326 has been recognized so that the associated set of ambiguity group effects 342 is output in **step** 116,
When the **pattern** 326 is recognized in **step** 114,, a new **pattern** recognition record 346 is developed and added to the input set 330, The matching performed in **step** 114 continues until all of the **pattern** recognition records, including those developed during the matching, have been compared to the failure model...

...numbers which
only have meanings relative to other ranking effects, The ranking effect for a **given** ambiguity group effect should therefore, be chosen to reflect the accuracy of the analysis.
In...the
structural model component with the greatest likelihood of failure, thereby avoiding unnecessary and lengthy **computations** .

In **addition** to the specification of system **characteristics** such as connectivity and hierarchy, the structural model 366 in accordance with a preferred embodiment...

...378
being associated with maintenance option 374, As before mentioned in describing step 122, the **actual** result 380 obtained in performing the maintenance option 374 can be compared to the expected 387 are confirmed by the **actual** results 380 and a second set
384, a first set 382 for use if the...

...the ambiguity group according to an associated ranking effect in step 106. Figure 8. for **example** , illustrates the case where the expected results 378 are confirmed by the **actual** results 380, so that the first set of ambiguity group effects 382 is selected to...

...can then be applied to the ambiguity group 364 in step 106, By way of **example** only, results obtained from the use of reliability statistics, Failure Modes and Effects analysis (FMEA...

...If any of the representations or models of the system under test are of low **quality** or if any **step** yields consistently poor results they occur more frequently in the case of heuristic rule based...description of plurality of components 412, 414 and 416, The model 410 includes static **characteristics** at location 418 for each component 412 to 416 as does the structured model 366, The static **characteristics** 418 describe the component repair profile,, in particular the testability and accessibility of the component, The maintenance options 420 through 424 which are output in **step** 120 of the preferred embodiment are also included here. These **characteristics** 416 can be used by a system technician to determine what to do next, Further...
...410 indicates that the component, The maintenance options 420 through 424 which are output in **step** 120 of the preferred embodiment are also included here. These **characteristics** 416 can be used by a system technician to determine what performed if the model...

...accessed via the ambiguity group pointers in the preferred embodiment of the invention. These static **characteristics** 416 can be substituted along with a static connectivity representation to construct the structural model...

...Component Model 410 is differentiated from the structural model 366 by the inclusion of dynamic **characteristics** of each component at locations 426 through 428. The dynamic **characteristics** at a particular location characterize the components connectivity, hierarchy, performance **characteristics** and function at a **given** phase or event within the system under test, The connectivity of the component is characterized...
...part of another group of components or consists of a group of components. The performance **characteristics** of the component are also included in its dynamic **characteristics** ,
To use the Event Structured Component Model 410, the operational history of the APU...

...the model 410 is further referenced by the determined phase of failure. So, for **example** , if component 2 ...determined to have occurred in phase I by analysis of the state vector obtained in **step** 102, then the dynamic **characteristics** of phase 1-of the second component at location 422 are accessed, These dynamic **characteristics** are used to recreate what the system should look like as compared to the **actual** operational **characteristics** are used to recreate what the system should

look like as compared to the **actual** operational **characteristics** of the system,
This procedure can be used to suggest further components to be analyzed...

...The knowledge representations, however, are system dependent and must be modified to represent the system **desired** to be analyzed.

An **example** of the diagnostic **tool** as applied to an Auxiliary Power Unit (APU) for an airplane is now **given** .

The application of the diagnostic **tool** to an APU is also described in "APU Maid: An Event - Based Model For Diagnosis...

...the units fuel, bleed air, lubrication and electrical systems,
Table 1 illustrates a single data **sample** having label DS200 which is collected during the operation of the APU.

The data **sample** provides six channels of analog data, including the time of the data **sample** , the oil pressure, the compressor discharge pressure, the fuel pressure, the **exhaust** gas temperature and the engine rpm. It also provides 16 channels of digital data as indicated.
TABLE 1: DATA **SAMPLE** -DS200
ANALOG
CHANNEL **PARAMETER** **VALUE** UNIT
TIME 2 -SEC
I P oil 2*1 PSI
Pcompressor discharge 0 PSI
3 P fuel 40,0 PSI
EGT (**exhaust** gas 10010 F
temperature)
%RPM (100% 39,000 RPM 11 %RPM
OVERSPEED 44,000 RPM
DIGITAL DISCRETE
CHANNEL **PARAMETER** **VALUE**
CENTRIFUGAL SWITCH (static test 1
...APU, the start of combustion within the APU, the reaction to the combustion and the **actual** combustion are shown,
TABLE 2: PARTIAL APU EVENT BASED REPRESENTATION
EVI1 - START EVENT
1) STATE VECTOR DEPENDENCIES
2) CRITICAL **PARAMETER** "START -SW" 1
3) AFFECTED **PARAMETERS**
twASRI# = 1
"APU-START RELAY" = 1
11APU-START MOTOR" = 1
"OVERSPEED-TEST-SOLENOID" = 1
11FHR11...

...AGE + 10
EV2 - COMBUSTION-START EVEN

1) STATE VECTOR DEPENDENCIES
START-EVENT - 1
2) CRITICAL **PARAMETERS**
P-OIL 2 - 3.5'PSI
%RPM GT 0
3) AFFECTED **PARAMETERS**
OIL-P-SEQ-SW 1
IGNITION-UNIT 1
TIME = LT 7 SEC
4) STATE VECTOR...

...10
EV3 COMBUSTION-REACT EMENT
1) STATE VECTOR DEPENDENCIES
COMBUSTION-START EVENT - 1
2) CRITICAL **PARAMETERS**
P-FUEL - GT 0 PSI
-3) AFFECTED **PARAMETERS**
-P-FUEL = 40 PSI
FUEL CONTROL VALVE SOL = 1
4) STATE VECTOR EFFECTS
EV3 - 1...

...AGE 10
EV4 - COMBUSTION EVENT
1) STATE VECTOR DEPENDENCIES
COMBUSTION-REACT EVENT = 1
2) CRITICAL **PARAMETER**
"EGT" GT 400 F
3) STATE VECTOR EFFECTS
EV4 = 1
IGNITION-UNIT = 1; AGE - 10...

...AGE + 10
Assume that Events 1 and 2 have been recognized by having their critical **parameters** matched by data **samples** prior to DS200, As a result of events 1 and 2 being recognized the state...

...recognition process of step 102 for event 3 is now described. Assume that the data **samples** prior to DS200 have already been compared to event 3. Data **sample** DS200 is now compared, The first step is to check the state vector dependencies, which...2 is listed as having occurred (EV2 = 1) so event recognition can continue. The critical **parameters** of Event 3, fuel pressure greater than 0 PSI (P fuel GT 0 PSI), is compared to data **sample** D8200 next, Analog channel 3 of DS200 indicates that fuel pressure is 40 PSI, greater...

...being recognized, event 3, is in the state vector, so that analysis of the data **sample** DS200 can now occur. The critical **parameter** for this event is that the **exhaust** gas temperature be greater than 400 F, Checking the data **sample** DS200 on analog channel number 4 it is seen that the 10 temperature is only 100 F. This event, therefore, is not recognized, Assume no other data **sample** serves to

recognized Event 4.
The recognized events as well as any events which were...

...to event 1 in Table 2, six components which are directly related to the critical **parameter** and the affected **parameterst** are listed, The appropriate ranking effect, in this case, is determined by referencing the data **sample** DS200 to confirm the state of the affected **parameters** defined in the state vettor effect. Consideringqthe first effected **parameter** pointed to by the state vector effect of event 1, the state of the start switch is already known since that was the critical **parameter** , the state of the APU start relay, digital channel number 9 of DS200 shows a discrete **value** of le This compares to the state of the affected **parameter** as listed in event 1, confirming the state vector effect so then the ambiguity group...

...greater than 40 PSI. To confirm this state vector effect, therefore, both of these affected **parameters** must be confirmed by data **sample** DS200.

Referring to analog channel 3, the fuel pressure is 40 PSI, confirming that affected **parameter** , Referring to digital channel 15, the fuel control valve solenoid activated (ml), confirming that affected **parameter** , Since the logical combination of affected **parameters** is satisfied, the state vector effect is confirmed. The associated ambiguity group effect absolving the...

...to DS200 in Table 1 it is seen that the ignition unit has a discrete **value** of 0, The associated ambiguity group that assigns a ranking effect of +10 is, therefore...

...associated with each component.

Table 5 illustrates a failure model which comprises two event **patterns** . The first event **pattern** is defined by three event criteria, EC1, EC2 and EC3, which must all occur event **pattern** 1 to be recognized, Event criteria 1 is further defined as the logical combination of...

...record 3
and not event record 4. Event criteria 2 is defined as the **pattern** recognition record which results from SF10 being recognized record which results from a'special test which is performed on the accelerator limiter. Associated with the first event **pattern** is an ambiguity effect which specifies the acceleration limiter as a suspect component and a ranking effect of + 10. The second event **pattern** is also defined by the three event criteria of above. Event criteria 1 and event criteria 2 are the same as above, however, event criteria 3 is a **pattern** recognition record 5 which results from special test which is performed on the ignition unit. The ambiguity effect associated with the second event **pattern** specifies that the ignition unit is suspect and assigns a ranking effect of +10. There are many

more event **patterns** in an APU failure model, however, only two are shown here,
If we assume that the results of the special test performed on the accelerator limiter is negative then event **pattern** 1 is not recognized. On the other hand if we assume that the results of the special test performed on the ignition unit is positive, then event **pattern** 2 is recognized and the associated ambiguity group effect, which specifies the ignition unit as...and analyzed event record, from each recognized symptom/fault relationship and from each recognized event **pattern** from the failure model and apply the ranking effectst the ambiguity group as shown in...

...result of the analysis of event 4 and as result of the recognition of event **pattern** 2 from the vary model,
TABLE 6: AMBIGUITY GROUP
AMBIGUITY GROUP RANKING (ALL COMPONENTS...was acquired for fault diagnosis,
It is preferable to use data acquisition circuitry having programmable **parameters** to allow for flexibility in the collection of the performance data. The following **parameters** , by way of **example** only, should be programmable; the enabling of the acquisition channels through which data is collected, the rate at which the data is **sampled** and the window of time over which the data is collected by the acquisition circuitry. Dynamically re-adjusting these and any other **parameters** provided by the acquisition circuitry according to the monitored performance of a system will yield...

...needs further analysis. Such a flexible data acquisition system will, therefore, yield data of improved **quality** as well as a greater quantity of relevant data.

Further, the data acquisition circuitry should...

...mentioned intelligent data acquisition module, product number AVME-9110, manufactured by Acromag, has programmable acquisition **parameters** and a Motorola 68000 microprocessor for controlling data acquisition, data storage and bus communications as...

...the system can be recognized.

Each of the event records in the database used in **step** 502 comprises critical **parameters** which define conditions which must occur during operation of the system for the event defined to the critical **parameters** and the state vector dependencies in the event based representation 152 at locations 160...

...The other data in the event bas4d representation 152 used for system diagnostics, the affected **parameters** and state vector effects, are not included in the representation used for monitoring,

Figure 12...

...recognition step 502 when monitoring a system's performance, In step 520, a first data **sample** from the data acquired during the step 500 is selected, In step 522, the first...

...recognition analysis for the selected event record continues. In the step 526, the selected data **sample** from the acquired data is compared to the critical **parameters** found in the selected event record. If a match between the critical **parameters** and the data **sample** is found in **step** 526, then the event defined by the event record is declared recognized in the step...

...the acquired data is examined in the step 536 to see if the last data **sample** from collected data was used. If it was, then the analysis is ended in the step 538. If there are more data **samples** , then the next one is retrieved in the step 540 and the analysis resumes starting...5the next event record is examined to see if it could have occurred during the **sample** window in which operational data was acquired. If it could not then the following event...

...event is recognized, with a minimum delay so that the monitoring can be performed in **real** time.

In the step 506, the data acquired in the step 500 is stored once...

...second event, which depends on the first recognized event, is recognized as normal, .Operational data **existing** during abnormal or missing events is, therefore, stored, The data can be stored using any...11 can also be used to improve the results obtained when performing fault diagnosis, For **example** , if the fault diagnostic procedures result in two components being equally ranked in their likelihood...

...of the additional data can then yield the faulty component. The results from the analysis **step** 508 can also-be used to modify a performance **parameter** in the system being monitored to improve the system's performance. For **example** , if in an airplane, a low fuel condition were detected, then the performance of the environmental control system could be **degraded** to conserve fuel.

Also, if the analysis performed in the **step** 508 indicates that the system is performing abnormally, then a warning can be issued to warn an operator of the system of the abnormal **behavior** . For **example** , if the system being monitored has military applications, an analysis process performing battle **damage** assessment on the system can use the results of system monitoring to determine the functionality...

...As mentioned before, the data acquisition system should be flexible to allow the modification of **parameters** within the data acquisition system in response to the **steps** 504 or 508. This is illustrated with reference to Figures 13 through 16, Figure...

...546, 548 and 550 are connected to the APU to detect the turbine RPM, the **Exhaust** Gas Temperature, the oil pressure, the fuel pressure and the compressor discharge pressure, respectively, A...

...digital convertor 556.

Whenever signals from the sensors 542 through 552 are acquired, a data **sample** record comprising each of the present signals is stored in a memory 558. Additionally, each data **sample** is time tagged in the memory 558, One of the advantages of this invention data acquisition system are illustrated, by way of **example** only,-to show the effectiveness of the present invention in obtaining data of better **quality** , The illustrated data acquisition system has twenty channels, a **given** amount of memory, for **example** 1 M byte or 8 M bitf and uses a twelve bit analog to digital...

...of data from the monitored system using this channel configuration 580 results in the data **sample** record 582. The data **sample** record 582 comprises 130 bits of data; twelve bits from each of the ten analog...

...a result, when the monitoring system uses the channel configuration 580 of Figure 14, 61538 **sample** records (18 M bits/130 bits per **sample** record) can be stored in the memory of the data acquisition system,
There may be...

...to an area of performance of the system which is of particular interest4 If. for **example** , the events recognized by the event recognition step 502 (see Figure 11) indicate that the...

...using the modified channel configuration 590 can be seen by referring to the resulting data **sample** 592, which comprises 28 bits; twelve bits from each of the two analog channels and...

...result, when the monitoring system uses the channel configuration 590 of Figure 15, 285,714 **sample** records (8 M bits/28 bits per **sample** record) can be stored in the memory of the data acquisition system,
The use of...

...channel configuration 590 of Figure 15, therefore, allows approximately 4,6 times the number of **sample** records to be stored as the use of the channel configuration 580 does, Furthermore, all...

...the aspect of performance of the system which
is of particular interest, whereas the data **sample** 582
resulting from the use of the channel configuration 580 ...interest, The
amount of relevant data stored is,
therefore, much greater than 4.6 times. **Given** the limited
amount of memory which can be provided in a **given** space,
this flexibility in channel configuration results in a
monitoring system with greatly improved data acquisition'.

both in terms of **quality** and quantity of data stored,
In **addition** to the channel configuration, the
sampling rate at which the data acquisition system **samples**
the signals in a system can be adjusted to examine a
particular aspect of the data. Figure 16 illustrates a
signal 620 which is **sampled** on a particular channel, A
first time line 622 illustrates the initial sampling rate of
the data-acquisition system, wherein **samples** of the signal
are taken at times t, and t3 and a voltage Level A...

...detailed picture of
the signal and to examine any transient responses in the
signal. For **example** , if the **sample** rate is doubled as
indicated on time line 624, so that the signal 620 is now
sampled at times t1, t2 and t3, then the **sample** taken at
time t2 would indicate an abnormal voltage Level B which was
undetected previously. Alternately, if the signal of
concern needs: to be **sampled** over a greater time window, the
sampling rate of-the system can be decreased,
Another...

Claim
... during its operation to obtain operational
data;
an event record data base for providing data
representative of a plurality of predefined events that
occur during operation of said system under test...

...predefined events
recognized by said comparison means;
a structural data base-for providing data
representative of said system under test's structure; and
analysis means for analyzing said structural data...

...as claimed in claim 6,
further comprising:
a first heuristic data base for providing data
representative of a plurality ...said listing in
said memory means according to components and ranking
effects associated with said **recognized** subset of
symptom-fault relationships.
8* A **fault diagnostic tool** as claimed in claim 7,
further comprising:
a second heuristic data base for providing data
representative of a plurality of failure modes-for said
symptom under test; and
third comparison means...

...the occurrence of said pre-defined event is dependent and by one or more critical **parameters** defining operational data which must occur during the system's performance for said pre-defined event to occur;
(b) acquiring a plurality of operational data **samples** from the system during a period of operation with a data acquisition system;
(c) for...

...plurality of event records, comparing a first of said plurality of said acquired operational data **samples** to said one or more critical **parameters** in said first of said plurality of event records, if a match is found...

...if a match is found between said first of said plurality of acquired operational data **samples** and said one or more critical **parameters** from said first of said plurality of event records and adding said recognized event to...

...of recognized events;
(f) repeating steps (d) and (e) for each successive acquired operational data **sample** in said plurality of acquired operational data **samples** unless said first of said plurality of event records is recognized in step (e);
(g claim 9, further comprising the **step** of:
(i) modifying a performance **parameter** in the system as a result of said analyzing **step** (h) to obtain a **desired** performance level of the system,

11 The method as claimed in claim 9, further comprising...

...modifying said data acquisition system to enable acquisition of a second plurality of operational data **samples** in accordance with the results of said analyzing step (h):

12 A method for monitoring...

...the occurrence of said pre-defined event is dependent and by one or more critical **parameters** defining operational data which must occur during the system's performance for said pre-defined...

...plurality of data defining actions to be performed;
(b) acquiring a plurality of operational data **samples** from the system during a period of operation with a data acquisition system;
(c) for...

...plurality of event records, comparing a first of said plurality of said

acquired operational data **samples** to sa@d one or more critical **parameters** in said first of said plurality of event records if a match is found in...

...if a match is found between said first of said plurality of acquired operational data **samples** and said one or more critical **parameters** from said first of said plurality of event records and adding said recognized event to...

...of recognized events;

(f) repeating steps (d) and (e) for each successive acquired operational data **sample** in said plurality of acquired operational data **samples** unless said first of said plurality of event records is recognized in step (e);

(g...from said step (h).

15 The method as claimed in claim 12, further comprising the **step** of:

M modifying a performance **parameter** in the system as a result of said analyzing **step** (h) to obtain a **desired** performance level of the system,

16 The method as claimed in claim 12, further comprising...

...modifying said data acquisition system to enable acquisition of a second plurality of operational data **samples** in accordance: with the results of said analyzing step (h):

17 Apparatus for monitoring a system's performance, comprising:

data acquisition means for collecting a plurality of operational data **samples** from the system during a period of operation;

an event record database for providing a...

...occurrence of said pre-defined event is dependent and by one or more critical **parameters** defining operational data which must occur during the system's performance for said pre-defined...

...is dependent and if a match is found, then comparing said one or more critical **parameters** to each successive operational data **sample** and if a match is found, recognizing said event pre-defined by said event record...

...The apparatus as claimed in claim 17, further comprising:

modifying means for changing a performance **parameter** in accordance with said an output from said analysis means.

19 The apparatus as claimed in claim 17, further comprising:

modifying means for adjusting one or more **parameters** in said data acquisition means in accordance with an output from said analysis means to enable acquisition of a second plurality of operational data **samples** .

```
Set     Items   Description
S1   15320629   PREDICT? OR INTUIT?? OR INTUITING OR FORECAST? OR PROGNOS?
             OR ANTICIPAT? OR EVALUAT? OR MONITOR? OR MEASUR?
S2   13667843   APPROXIMATING OR CALCULAT? OR COMPUTING OR COMPUTE OR COMP-
             UTES OR COMPUTED OR ESTIMAT? OR APPRAIS? OR ASSESS? OR TREND?-
             (3N)ANALY? OR INTERPOLAT? OR RECOGNI? OR EXTRAPOLAT? OR DERIV?
S3    7127940   S1:S2(7N)(METHOD? OR SYSTEM? OR PROCESS?? OR PROCEDUR? OR -
             TECHNIQUE? OR MODE?)
S4     165605   (REMAINING? OR REMAINDER? OR AVAILAB? OR LEFT OR RESIDUAL?-
             )(5N)(LIFE? OR YEAR? OR TIME? OR DAY OR DAYS OR HOUR? OR WEEK?
              OR MONTH?)
S5     392535   TIME(2W)FAILURE? OR FAULT?(2W)DIAGNOS? OR TIME(2W)OPERATIO-
             N? OR (WORK? OR OPERATION?)(2N)LIFE? OR BREAKDOWN? OR (BREAK?
             OR BROKE?)()DOWN
S6       1084   (VIRTUAL? OR THEORETIC?)(2N)(AGE OR AGES OR AGING)
S7   12904293   MACHIN? OR EQUIPMENT? OR APPLIANC? OR APPARATUS? OR TOOL? ?
              OR ENGINE? OR INDUSTR?()DEVICE? OR MECHANIC? OR MECHANISM?
S8    2083953   *deleted*  WEAR? OR DAMAG? OR ATTRIT? OR EROSI? OR ERODE? -
             OR ERODING OR ABRAD? OR DEGENERAT? OR DECLIN? OR WORSEN?
S9    4092398   *deleted*  DELAPIDAT? OR EXHAUST? OR FATIGU? OR DEGRAD? OR
             DETERIORAT? OR ABRAS? OR DECAY? OR DIMINISH? OR STRESS?
S10  13635225   *deleted*  PARAMETER? OR VARIABL? OR VALUE? OR QUALITY? OR
             QUALITIE? OR CHARACTERISTIC? OR THRESHOLD?
S11  10609049   *deleted*  ATTRIBUT? OR TRAIT? OR PATTERN? OR COEFFICIENT?
             OR BEHAVIOR? OR BEHAVIOUR? OR VECTOR?
S12  11560711   *deleted*  INCREMENT? OR STEP OR STEPS OR STEPPED OR STEPP-
             ING OR AUGMENTAT? OR INCREAS? OR UPTICK? OR UP()TICK? OR ADDI-
             TION? OR ADVANC? OR PROGRESSION? OR PROGRESSING? OR STEP(2W)S-
             TEP OR STEPWISE? OR BIT(2W)BIT OR INCH(2W)INCH OR PIECEMEAL?
S13    736967   *deleted*  DECREMENT? OR PROTOCOL? OR GRADATION? OR GRADUA-
             T? OR CUMULATIV?
S14    770369   *deleted*  NEURAL()NETWORK? OR MACHINE()(LEARN? OR INTELLI-
             GEN?) OR ARTIFICIAL()INTELLIGEN? OR AI OR GAUSS?()(DISTRIBUT?
             OR CURVE?) OR FUZZY()(LOGIC? OR INFERENC? OR THEOR?)
S15     51496   *deleted*  RADIAL()BASIS OR BASIS()FUNCTION? OR RBF OR RAD-
             IALBASIS? OR BASISFUNCTION? OR RBFN
S16         0   *deleted*  COVER?(2N)THEOREM?(5N)SEPARAB?(5N)PATTERN?
S17         8   *deleted*  (INPUT?(10N)OUTPUT?)(10N)(MAP OR MAPS)(10N)(APP-
             ROXIMATOR? OR APPROXIMATER?)
S18     88146   S1:S3 AND S4:S6 AND S7
S19    770369   NEURAL()NETWORK? OR MACHINE()(LEARN? OR INTELLIGEN?) OR AR-
             TIFICIAL()INTELLIGEN? OR AI OR GAUSS?()(DISTRIBUT? OR CURVE?)
             OR FUZZY()(LOGIC? OR INFERENC? OR THEOR?)
S20     51496   RADIAL()BASIS OR BASIS()FUNCTION? OR RBF OR RADIALBASIS? OR
              BASISFUNCTION? OR RBFN
S21         0   COVER?(2N)THEOREM?(5N)SEPARAB?(5N)PATTERN?
S22         8   (INPUT?(10N)OUTPUT?)(10N)(MAP OR MAPS)(10N)(APPROXIMATOR? -
             OR APPROXIMATER?)
S23        23   (APPROXIMATOR? OR APPROXIMATER?)(10N)LINEAR?(3N)(COMBINE? -
             OR COMBINING? OR COMBINATION?)
S24      5321   S18 AND S19:S23
S25       209   S24 AND S19 AND S20
S26        92   S25 AND PY<2001
S27        79   RD (unique items)
File   2:INSPEC 1969-2005/Jul W4
         (c) 2005 Institution of Electrical Engineers
File   6:NTIS 1964-2005/Jul W4
         (c) 2005 NTIS, Intl Cpyrght All Rights Res
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         (c) 2005 Elsevier Eng.  Info. Inc.
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         (c) 2005 Inst for Sci Info
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File  95:TEME-Technology & Management 1989-2005/Jun W4
         (c) 2005 FIZ TECHNIK
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         (c) 2005 The HW Wilson Co.
File 111:TGG Natl.Newspaper Index(SM) 1979-2005/Aug 03
         (c) 2005 The Gale Group
File 144:Pascal 1973-2005/Jul W4
         (c) 2005 INIST/CNRS
File 239:Mathsci 1940-2005/Sep
         (c) 2005 American Mathematical Society
File 256:TecInfoSource 82-2005/Jun
         (c) 2005 Info.Sources Inc
File 434:SciSearch(R) Cited Ref Sci 1974-1989/Dec
         (c) 1998 Inst for Sci Info
?
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27/3,K/6 (Item 6 from file: 2)
DIALOG(R)File 2:INSPEC

6507356 INSPEC Abstract Number: B2000-04-6140-002, C2000-04-7440-001
Title: Diagnosis of rolling element bearing faults using radial basis function **networks**
Author(s): Jack, L.B.; Nandi, A.K.; McCormick, A.C.
Author Affiliation: Dept. of Electr. Eng. & Electron., Liverpool Univ., UK
Journal: Applied Signal Processing vol.6, no.1 p.25-32
Publisher: Springer-Verlag,
Publication Date: 1999 Country of Publication: UK
CODEN: ASPRFL ISSN: 0941-0635
SICI: 0941-0635(1999)6:1L.25:DREB;1-F
Material Identity Number: A479-2000-001
U.S. Copyright Clearance Center Code: 0941-0635/99/$2.00+0.20
Language: English
Subfile: B C

Title: Diagnosis of rolling element bearing faults using radial basis function **networks**
Abstract: There are many techniques for extracting indicators of a **machine** 's condition from its vibrations. In detecting common **machine** problems such as bearing defects, a combination of several indicators may provide the best diagnosis. Artificial **neural networks** provide a way of combining this information, giving improved **fault diagnosis** . The selection of the best combination of complementary features is not, however, straightforward, especially as...

... was subjected to a number of common rolling element bearing faults and different features were **estimated** from **measured** vibrations. **Radial basis function** networks were trained and **evaluated** for a large number of possible combinations of input features. This allowed the determination of those features which were useful in fault **recognition** and characterisation, and those which provided little or no useful information at all.
...Descriptors: condition **monitoring** ; ...

... **fault diagnosis** ; ...

...learning (**artificial intelligence**); ...

... **machine** bearings...

... **mechanical engineering computing** ; ...
...parameter **estimation** ; ...

... **radial basis function** networks...

...vibration **measurement**
Identifiers: **fault diagnosis** ; ...

... **radial basis function** networks...

... **machine** condition...

...artificial **neural networks** ; ...

...feature **estimation** ; ...

...vibration **measurement** ;
1999

27/3,K/7 (Item 7 from file: 2)
DIALOG(R)File 2:INSPEC

6498269 INSPEC Abstract Number: C2000-03-5290-013
Title: Fault detection of rotating machine **parts using novel fuzzy** neural network
Author(s): Taniguchi, S.; Akhmetov, D.; Dote, Y.
Author Affiliation: Dept. of Comput. Sci. & Syst. Eng., Muroran Inst. of Technol., Hokkaido, Japan
Conference Title: IEEE SMC'99 Conference Proceedings. 1999 IEEE International Conference on Systems, Man, and Cybernetics (Cat. No.99CH37028) Part vol.1 p.365-9 vol.1
Publisher: IEEE, Piscataway, NJ, USA
Publication Date: 1999 Country of Publication: USA 6 vol. (1179+1075+1106+1124+1140+1078) pp.
ISBN: 0 7803 5731 0 Material Identity Number: XX-1999-03282
U.S. Copyright Clearance Center Code: 0 7803 5731 0/99/$10.00
Conference Title: IEEE SMC'99 Conference Proceedings. 1999 IEEE International Conference on Systems, Man, and Cybernetics
Conference Sponsor: IEEE Syst., Man, & Cybernetics Soc. (SMC); Sci. Council of Japan (SCJ); Soc. Instrum. & Control Eng. (SICE); Robotics Soc. Japan (RSJ); Japan Soc. Mech. Eng. (JSME)
Conference Date: 12-15 Oct. 1999 Conference Location: Tokyo, Japan
Language: English
Subfile: C

Title: Fault detection of rotating machine **parts using novel fuzzy** neural network
Abstract: This paper proposes a novel fuzzy **neural network** for fault detection of rotating **machine** parts. Firstly, soft **computing** which is the fusion or combination of fuzzy systems, **neural networks** and genetic algorithms is studied. Then, by taking advantages of fuzzy systems and **neural networks** a novel fuzzy- **neural network** with a general parameter learning algorithm and system structure determination is developed. The network is based on one of local **basis function** networks. The general parameter method (GP) is based on GMDH (group methods of data handling...

... GP is used for a learning algorithm and the structure determination of the developed fuzzy **neural network** . As the resulting network needs only **fuzzy inference** computation with GP **calculations** , which is, generally speaking, the combination of soft and hard **computing** , called computational intelligence, is suitable to solve nonlinear problems, it especially needs a little computation...
... it is easy to implement with a HITACHI RISC+DSP microprocessor fast enough for real **time operations** . The developed signal processor is self-organizing, self-tuning and automated designed. In order to confirm the feasibility of **fault diagnosis** performance by the developed network, it is experimentally applied to **fault** detection (**diagnosis**) of rotational **machine** parts (automobile transmission gears). It is found that the developed method is superior to other...
...Descriptors: **fault diagnosis** ; ...

...inference **mechanisms** ;
Identifiers: fuzzy **neural network** ; ...

...rotating **machine** parts...

...soft **computing** ; ...

...local **basis** **function** networks...

... **fuzzy** **inference** computation...

...real **time** **operations** ;
1999

27/3,K/8 (Item 8 from file: 2)
DIALOG(R)File 2:INSPEC

6489864 INSPEC Abstract Number: B2000-03-7620-014, C2000-03-7460-033
Title: Automated rule extraction for engine **vibration analysis**
Author(s): Brotherton, T.; Chadderdon, G.; Grabill, P.
Author Affiliation: Orincon Corp., San Diego, CA, USA
Conference Title: 1999 IEEE Aerospace Conference. Proceedings (Cat. No.99TH8403) Part vol.3 p.29-38 vol.3
Publisher: IEEE, Piscataway, NJ, USA
Publication Date: 1999 Country of Publication: USA 5 vol. (xiv+488+492+470+466+480) pp.
ISBN: 0 7803 5425 7 Material Identity Number: XX-1999-02384
Conference Title: 1999 IEEE Aerospace Conference. Proceedings
Conference Sponsor: IEEE Aerosp. & Electron. Syst. Soc
Conference Date: 6-13 March 1999 Conference Location: Snowmass at Aspen, CO, USA
Language: English
Subfile: B C

Title: Automated rule extraction for engine **vibration analysis**
Abstract: A problem in **engine** health **monitoring** is the automatic detection and classification of potential component failures. Current processing uses simple features to **measure** and characterize changes in sensor data. An alternative solution uses **neural networks** coupled with appropriate feature extractors. Unfortunately most neural nets give little insight into the "why" of their output decisions. We have developed a variation of the **radial basis function** neural net for the problem. The neural net is essentially a nearest neighbor classifier. Classification rules can be found by examination of the **basis functions** . Rule complexity is reduced by using evolutionary programming to select the input features and neural...

...that gives superior performance when compared to a traditional approach.. The approach is a valuable **tool** for developing simple rules when a large feature set is available.
Descriptors: aerospace **engines** ; ...

... **fault diagnosis** ; ...

...vibration **measurement**
...Identifiers: **engine** vibration analysis...

... **neural networks** ; ...
... **interpolation**
1999

27/3,K/9 (Item 9 from file: 2)
DIALOG(R)File 2:INSPEC

6485781 INSPEC Abstract Number: C2000-03-1230D-029
Title: Design of fault diagnostic **system based on neuro-fuzzy scheme**
Author(s): Sung-Ho Kim; Jung-Soo Kim; Taehong Park; Jong-Ryeol Lee; Gwi-Tae Park
Journal: Transactions of the Korean Institute of Electrical Engineers, A vol.48, no.10 p.1272-8
Publisher: Korean Inst. Electr. Eng,
Publication Date: Oct. 1999 Country of Publication: South Korea
CODEN: CHNODD ISSN: 1229-2443
SICI: 1229-2443(199910)48:10L.1272:DFDS;1-4
Material Identity Number: H329-1999-010
Language: Korean
Subfile: C

Title: Design of fault diagnostic **system based on neuro-fuzzy scheme**
...Abstract: parameter identification of a nonlinear system and to the association of the set of the **estimated** parameters with the **mode** of faults. A neuro- **fuzzy inference** system which contains multiple linear models as consequent part is used to model nonlinear systems. Generally, the linear parameters in neuro- **fuzzy inference** system can be effectively utilized to **fault diagnosis** . In this paper, the author proposes an FDI system for nonlinear systems using neuro- **fuzzy inference** system. The proposed diagnostic system consists of two neuro- **fuzzy inference** systems which operate in two different modes (parallel and series-parallel mode). It generates the parameter residuals associated with each modes of faults which can be further processed by additional **RBF** (**radial basis function**) network to identify the faults. The proposed FDI scheme has been tested by simulation on...
Descriptors: **fault diagnosis** ; ...

...inference **mechanisms** ; ...

...parameter **estimation** ; ...

... **radial basis function** networks
Identifiers: **fault diagnostic** system design...

...neuro- **fuzzy inference** system...

... **radial basis function** network
1999

27/3,K/10 (Item 10 from file: 2)
DIALOG(R)File 2:INSPEC

6439875 INSPEC Abstract Number: B2000-01-1205-012, C2000-01-7410D-121
Title: Application of radial basis function **network to the preventive maintenance of electronic analog circuits**
Author(s): Catelani, M.; Fort, A.; Nosi, G.
Author Affiliation: Dipt. di Ingegneria Electron., Florence Univ., Italy
Conference Title: IMTC/99. Proceedings of the 16th IEEE Instrumentation and Measurement Technology Conference (Cat. No.99CH36309) Part vol.1 p.510-13 vol.1
Editor(s): Piuri, V.; Savino, M.
Publisher: IEEE, Piscataway, NJ, USA
Publication Date: 1999 Country of Publication: USA 3 vol.xl+1937 pp.
ISBN: 0 7803 5276 9 Material Identity Number: XX-1999-01871
U.S. Copyright Clearance Center Code: 0 7803 5276 9/99/$10.00
Conference Title: IMTC/99. Proceedings of the 16th IEEE Instrumentation and Measurement Technology Conference. Measurements for the New Millennium
Conference Sponsor: IEEE Instrum. & Meas. Soc
Conference Date: 24-26 May 1999 Conference Location: Venice, Italy
Language: English
Subfile: B C

Title: Application of radial basis function **network to the preventive maintenance of electronic analog circuits**
...Abstract: detect soft fault is an important task in the preventive maintenance. In this paper a **neural network** based approach to fault detection of both linear and non linear circuits is presented. In particular **Radial Basis Functions** (**RBF**) networks are used to analyse circuit input-output **measurements** , and to localise faulty element. These **methods** exploit the capabilities, typical of **neural networks** , to analyze and classify signatures acid to deal with problems involving poorly defined system models...
...Descriptors: circuit analysis **computing** ; ...

... **fault diagnosis** ; ...

...maintenance **engineering** ; ...

... **radial basis function** networks
Identifiers: **radial basis function** network...

... **neural network** ; ...

...input-output **measurements** ;
1999

27/3,K/13 (Item 13 from file: 2)
DIALOG(R)File 2:INSPEC

6234910 INSPEC Abstract Number: B1999-06-8310-010, C1999-06-7410B-028
Title: **Pattern** recognition **and diagnosis of faults in electrical** machines
Author(s): Qiu Arui; Sun Jian
Author Affiliation: Dept. of Electr. Eng., Tsinghua Univ., Beijing, China
Journal: Journal of Tsinghua University (Science and Technology) vol.39, no.3 p.72-4
Publisher: Tsinghua Univ,
Publication Date: March 1999 Country of Publication: China
CODEN: QDXKE8 ISSN: 1000-0054
SICI: 1000-0054(199903)39:3L.72:PRDF;1-D
Material Identity Number: G276-1999-004
Language: Chinese
Subfile: B C

Title: **Pattern** recognition **and diagnosis of faults in electrical** machines
Abstract: In order to automatically **recognize** and diagnose the fault patterns of electrical **machines** , a pattern **recognition method** by using an artificial **neural network** is developed based on the analysis of both the classification characteristics of artificial **neural networks** and the traditional technology of **fault diagnosis** of electrical **machines** . For cases that the fault patterns are nonlinear separable, a **radial - basis function** (**RBF**) network is adopted as by using a phi -function a nonlinear separable pattern can be...

... classification. Test results on the rotor faults of induction motors show that this fault pattern **recognition method** by using the **RBF** network can not only be effective, but also improve the average probability of correct classification by a supervised selection of centers of the **RBF** network.
Descriptors: electric **machine** analysis **computing** ; ...

... **fault diagnosis** ; ...

...pattern **recognition** ; ...

... **radial basis function** networks
...Identifiers: artificial **neural network** ; ...

... **RBF** network
1999

27/3,K/14 (Item 14 from file: 2)
DIALOG(R)File 2:INSPEC

6202756 INSPEC Abstract Number: C1999-05-7470-006
Title: Fault diagnosis **of a nuclear processing plant using** neural networks
Author(s): Weerasinghe, M.; Williams, D.; Gomm, J.B.
Author Affiliation: Control Syst. Res. Group, Liverpool Moores Univ., UK
Conference Title: Control of Industrial Systems. `Control for the Future of the Youth'. Proceedings volume form the IFAC Conference Part vol.2 p.977-82 vol.2
Editor(s): Grujic, L.T.; Borne, P.; Moudni, A.E.; Ferney, M.
Publisher: Pergamon, Oxford, UK
Publication Date: 1997 Country of Publication: UK 3 vol. xxvii+1682 pp.
ISBN: 0 08 042907 6 Material Identity Number: XX-1999-00581
Conference Title: Proceeding of Conference 97. IFAC IFIP IMACS. On Control of Industrial Systems
Conference Sponsor: IFAC; Assoc. Francaise pour la Cybern., Econ. Tech.; IFIP; IMACS
Conference Date: 20-22 May 1997 Conference Location: Belfort, France
Language: English
Subfile: C

Title: Fault diagnosis **of a nuclear processing plant using** neural networks
Abstract: Development of a reliable **fault diagnosis** method for a large scale industrial plant is laborious and often difficult to achieve due to the complexity of the systems. The application of **neural networks** to the diagnosis of non-catastrophic faults on an industrial nuclear processing plant is described...

... and principal component analysis, are investigated to facilitate fault classification and reduce the complexity of **neural networks** . Results are presented to illustrate the performance of trained **neural networks** for classifying process faults using real data.
...Descriptors: **fault diagnosis ;** ...

...nuclear **engineering computing ;** ...

... **radial basis function** networks
Identifiers: **fault diagnosis ;** ...

... **RBF neural networks ;**
1997

27/3,K/21 (Item 21 from file: 2)
DIALOG(R)File 2:INSPEC

5636600 INSPEC Abstract Number: B9708-8230F-005, C9708-7410B-157
Title: Utilising a SIMULINK gas turbine engine **model for** fault diagnosis
Author(s): Patel, V.C.; Kadirkamanathan, V.; Thompson, H.A.; Fleming, P.J.
Author Affiliation: Sheffield Univ., UK
Conference Title: Control of Power Plants and Power Systems (SIPOWER'95). A Proceedings volume from the IFAC Symposium p.237-42
Editor(s): Canales-Ruiz, R.
Publisher: Pergamon, Oxford, UK
Publication Date: 1996 Country of Publication: UK xi+542 pp.
ISBN: 0 08 042362 0 Material Identity Number: XX95-01612
Conference Title: International Symposium on Control of Power Plants and Power Systems
Conference Sponsor: IFAC
Conference Date: 6-8 Dec. 1995 Conference Location: Cancun, Mexico
Language: English
Subfile: B C

Title: Utilising a SIMULINK gas turbine engine **model for** fault diagnosis
Abstract: Gas turbine **engines** are highly nonlinear, multi-sample rate, multi-input/multi-output systems with fast changing dynamics. As a consequence a representative gas turbine **engine** model that comprises the **engine** , its accessories and the controller, is extremely complex and interactive, incorporating look-up tables **derived** from real **engine** data and a mixture of continuous and logical functions. In this paper, a SIMULINK model of the gas turbine **engine** and controller is described. This model is being primarily used for generating simulated fault data that is being used to train **neural networks** for **fault diagnosis** . The current work focuses on using resource allocating networks (RAN) to not only identify faults...
Descriptors: **fault diagnosis** ; ...

...learning (**artificial intelligence**); ...

...power **engineering computing** ;
Identifiers: SIMULINK gas turbine **engine** model...

... **fault diagnosis** ; ...

... **neural networks** training...

... **radial basis function** networks
1996

27/3,K/22 **(Item 22 from file: 2)**
DIALOG(R)File 2:INSPEC

5536221 INSPEC Abstract Number: C9705-7400-005
Title: Fault diagnosis **of dynamic systems using ANN-based MMAE method**
Author(s): Zhang, Y.; Li, Q.; Dai, G.; Frank, P.M.
Author Affiliation: Dept. of Autom. Control, Northwestern Polytech. Univ., Xian, China
Journal: Elektronnoe Modelirovanie vol.18, no.5 p.38-48
Publisher: Inst. Problem NAN Ukrainy,
Publication Date: Sept.-Oct. 1996 Country of Publication: Ukraine
CODEN: ELMODO ISSN: 0204-3572
SICI: 0204-3572(199609/10)18:5L.38;1-E
Material Identity Number: E296-97002
Translated in: Electronic Modeling
Country of Publication: UK
CODEN: EMODD8 ISSN: 0275-9136
Language: English
Subfile: C

Title: Fault diagnosis **of dynamic systems using ANN-based MMAE method**
Abstract: The paper combines a **neural network** (ANN) and a multiple **model** adaptive **estimator** (MMAE) to realize a new approach for **fault** detection and **diagnosis** (FDD) of nonlinear systems as well as linear systems. Instead of Kalman filter, a bank of ANNs is inserted in the MMAE, forming a group of nonlinear **estimators** . In order to overcome the drawbacks of traditional training algorithms for **radial basis function** networks (**RBFN**), a new optimization and training method based on the singular value decomposition (SVD) technique for **RBFN** is developed . The new algorithm is then used for FDD of nonlinear systems as well...
Descriptors: adaptive **estimation** ; ...

... **engineering computing** ; ...

... **fault diagnosis** ;
Identifiers: **fault diagnosis** ; ...

... **neural network** ; ...

...multiple **model** adaptive **estimator** ; ...

...nonlinear **estimators** ; ...

... **radial basis function** networks
1996

27/3,K/25 **(Item 25 from file: 2)**
DIALOG(R)File 2:INSPEC

5506591 INSPEC Abstract Number: C9704-7450-002
Title: Lime kiln fault **detection and** diagnosis **by** neural networks
Author(s): Ribeiro, B.; Costa, E.; Dourado, A.
Author Affiliation: Centro de Inf. e Sistemas, Coimbra Univ., Portugal
Conference Title: Artificial Neural Nets and Genetic Algorithms. Proceedings of the International Conference p.112-15
Editor(s): Pearson, D.W.; Steele, N.C.; Albrecht, R.F.
Publisher: Springer-Verlag, Vienna, Austria
Publication Date: 1995 Country of Publication: Austria xv+528 pp.
ISBN: 3 211 82692 0 Material Identity Number: XX95-00357
Conference Title: Proceedings of International Conference on Artificial Neural Networks and Genetic Algorithms
Conference Date: 18-21 April 1995 Conference Location: Ales, France
Language: English
Subfile: C

Title: Lime kiln fault **detection and** diagnosis **by** neural networks
Abstract: Artificial **neural networks** have recently been used successfully for **fault** detection and **diagnosis** in chemical processes. We present a study on **fault** detection and **diagnosis** of an industrial lime kiln which is a complex highly nonlinear process within the pulp and paper industry. We show the capability of **neural networks** to learn faults which can occur during steady state kiln operation, their adaptation to different...

... capability to spontaneously generalize. We compare the performance of two architectures, namely BPNN (Back Propagation **Neural Network**) and RBFNN (**Radial Basis Function Neural Network**), and investigate several topologies. Through this study, it can be concluded that the RBFNN architecture...
...Descriptors: chemical **engineering computing** ; ...

... **fault diagnosis** ;
...Identifiers: **fault diagnosis** ; ...

...artificial **neural networks** ; ...

...Back Propagation **Neural Network** ; ...

... **Radial Basis Function Neural Network** ;
1995

27/3,K/27   (Item 27 from file: 2)
DIALOG(R)File   2:INSPEC

5444410   INSPEC Abstract Number: C9701-7440-059
Title: **A** RBF neural network **model for cylinder pressure reconstruction in internal combustion** engines
Author(s): Gu, F.; Jacob, P.J.; Ball, A.D.
Author Affiliation: Sch. of Eng., Manchester Univ., UK
Conference Title: IEE Colloquium on Modelling and Signal Processing for Fault Diagnosis (Ref. No.1996/260)   p.4/1-11
Publisher: IEE, London, UK
Publication Date: 1996 Country of Publication: UK   100 pp.
Material Identity Number: XX96-03400
Conference Title: IEE Colloquium on Modelling and Signal Processing for Fault Diagnosis (Ref. No.1996/260)
Conference Sponsor: IEE
Conference Date: 18 Sept. 1996   Conference Location: Leicester, UK
Language: English
Subfile: C

Title: **A** RBF neural network **model for cylinder pressure reconstruction in internal combustion** engines
Abstract: This paper proposes the use of a non-parametric **RBF neural network** to model the relationship between the instantaneous angular velocity of the crankshaft and the pressure in the cylinders of an internal combustion **engine** . The structure of the model and the training procedure of the network is outlined. The application of the model is demonstrated on a four cylinder DI diesel **engine** with data from a wide range of speed and load settings. The **prediction** capabilities of the **model** once trained can be validated against **measured** data. An example is given of the application of this model to aid in the...
Descriptors: angular velocity **measurement** ; ...

... **fault diagnosis** ; ...

...internal combustion **engines** ; ...

...pattern **recognition** ;
Identifiers: **RBF neural network** model...

...internal combustion **engines** ; ...

...nonparametric **neural network** ; ...

...four cylinder DI diesel **engine** ; ...

... **prediction** capabilities
1996

27/3,K/29 (Item 29 from file: 2)
DIALOG(R)File 2:INSPEC

5357723 INSPEC Abstract Number: B9610-8130-006, C9610-7410B-053
Title: Radial basis function neural networks **for** fault diagnosis **in series compensated transmission lines: a comparison study**
Author(s): Song, Y.H.; Xuan, Q.Y.; Johns, A.T.; Aggarwal, R.K.
Author Affiliation: Sch. of Electron. & Electr. Eng., Bath Univ., UK
Conference Title: IIA'96/SOCO'96. International ICSC Symposia on Intelligent Industrial Automation and Soft Computing p.B121-5
Editor(s): Anderson, P.G.; Warwick, K.
Publisher: Int. Comput. Sci. Conventions, Millet, Alta., Canada
Publication Date: 1996 Country of Publication: Canada ix+556 pp.
ISBN: 3 906454 01 0 Material Identity Number: XX96-00941
Conference Title: Proceedings of IIA '96. Intelligent Industrial Automation
Conference Date: 26-28 March 1996 Conference Location: Reading, UK
Language: English
Subfile: B C

Title: Radial basis function neural networks **for** fault diagnosis **in series compensated transmission lines: a comparison study**
Abstract: Since the complex variation of line impedance is accentuated as the capacitor's own protection **equipment** operates randomly under fault conditions in series compensated transmission systems, conventional distance protection schemes are...

... perceptrons. The basic idea of the method is to design a protection scheme using a **neural network** approach by catching the feature signals in a certain frequency range under fault conditions. This is different from conventional schemes that are based on **deriving** implicit mathematical equations based on the information obtained by complex filtering techniques. This paper presents some recent results of employing different types of **neural networks** for this particular application. The performances of three **neural networks** have been analyzed and compared, including: (i) backpropagation network (BP); (ii) **radial basis function** network (**RBFN**) and (iii) counter-propagation network (CP). The study shows that CP and **RBFN** have better performance than the commonly used BP network. As fault identification is only part of the protection scheme, further work is towards the development of a completed **neural network** based protection technique.
...Descriptors: **fault diagnosis ;** ...

...power **engineering computing ;**
Identifiers: **radial basis function neural networks ;** ...
... **fault diagnosis ;** ...

...protection **equipment ;**
1996

27/3,K/34 (Item 34 from file: 2)
DIALOG(R)File 2:INSPEC

4987519 INSPEC Abstract Number: C9508-1230-031
Title: Learning methodology for failure detection and accommodation
Author(s): Polycarpou, M.M.; Vemuri, A.T.
Author Affiliation: Dept. of Electr. & Comput. Eng., Cincinnati Univ., OH, USA
Journal: IEEE Control Systems Magazine vol.15, no.3 p.16-24
Publication Date: June 1995 Country of Publication: USA
CODEN: ISMAD7 ISSN: 0272-1708
U.S. Copyright Clearance Center Code: 0272-1708/95/$04.00
Language: English
Subfile: C

...Abstract: fault tolerance in dynamical systems many algorithms have been developed during the past two decades. **Fault diagnosis** and accommodation methods have traditionally been based on linear modeling techniques, which restricts the type...

... learning methodology for failure detection and accommodation. The main idea behind this approach is to **monitor** the physical **system** for any off-nominal behavior in its dynamics using nonlinear modeling techniques. The principal design **tool** used is a generic function approximator with adjustable parameters, referred to as online approximator. Examples of such structures include traditional approximation models such as polynomials and splines as well as **neural networks** topologies such as sigmoidal multilayer networks and **radial basis function** networks. Stable learning **methods** are developed for **monitoring** the dynamical **system** . The nonlinear **modeling** nature and learning capability of the **estimator** allow the output of the online approximator to be used not only for detection but...

... and to gain intuition into the effect of modeling uncertainties on the performance of the **fault diagnosis** scheme.
...Descriptors: **fault diagnosis** ; ...

...learning (**artificial intelligence**);
...Identifiers: **neural network** topologies...

... **radial basis function** networks
1995

27/3,K/35 (Item 35 from file: 2)

4974031 INSPEC Abstract Number: C9507-5290-061
Title: **An adaptive** neural network **for on-line learning and diagnosis of process faults**
Author(s): Gomm, J.B.; Wiiliams, D.
Author Affiliation: Sch. of Electr. & Electron. Eng., Liverpool John Moores Univ., UK
p.9/1-5
Publisher: IEE, London, UK
Publication Date: 1995 Country of Publication: UK 90 pp.
Conference Title: IEE Colloquium on 'Qualitative and Quantitative Modelling Methods for Fault Diagnosis' (Digest No.1995/079)
Conference Sponsor: IEE
Conference Date: 24 April 1995 Conference Location: London, UK
Language: English
Subfile: C

Title: **An adaptive** neural network **for on-line learning and diagnosis of process faults**
Abstract: Techniques to enable a **radial basis function** (**RBF**) network to exhibit online learning properties for process **fault diagnosis** are described. These methods were demonstrated in an application of the **RBF** network to the diagnosis of a range of both sudden and gradual faults in a simulated continuous stirred tank reactor (CSTR) **process** . The network was able to **recognise** and learn new fault conditions recursively, and also to successfully diagnose faults that had been previously encountered. The results demonstrate the potential of the approach for online **fault diagnosis** applications in real processes. The network can be considered as a type of **process** fault **model** which maps the **process measurement** space to a fault classification space. The network centres represent points in the **process measurement** space which correspond to transient and steady-state features of faults on the process. Further...
Descriptors: chemical **engineering computing** ; ...

... **fault diagnosis** ; ...

...learning (**artificial intelligence**);
Identifiers: adaptive **neural network** ; ...

...online **fault diagnosis** ; ...

...process **fault diagnosis** ; ...

... **radial basis function** network...

...recursive fault condition **recognition** ; ...

... **process measurement** space
1995

27/3,K/36 (Item 36 from file: 2)
DIALOG(R)File 2:INSPEC

4971817 INSPEC Abstract Number: B9507-8110B-099, C9507-7410B-271
Title: Fault diagnosis **and** neural networks : **a power plant application**
Author(s): Guglielmi, G.; Parisini, T.; Rossi, G.
Author Affiliation: UF/D/Q Dept., CSELT, Torino, Italy
Journal: Control Engineering Practice vol.3, no.5 p.601-20
Publication Date: May 1995 Country of Publication: UK
CODEN: COEPEL ISSN: 0967-0661
U.S. Copyright Clearance Center Code: 0967-0661/95/$9.50+0.00
Language: English
Subfile: B C
Copyright 1995, IEE

Title: Fault diagnosis **and** neural networks : **a power plant application**
Abstract: Correct and timely fault detection is of major importance in the field of system **engineering** , and constitutes a primary problem in a broad spectrum of cases, from industrial processes to high-performance systems and to mass-produced consumer **equipment** . A large number of methods can be found in the literature, and the recent use of **neural networks** for solving **fault - diagnosis** problems in real industrial situations seems to be particularly promising. This paper describes a neural approach to solving approximately some very difficult **fault - diagnosis** problems. A real system (the four heaters of a feedwater high-pressure line of a...

... accurate and validated model of the plant show the effectiveness of using multilayer feedforward and **Radial Basis Function neural networks** to solve real **fault** -detection and **diagnosis** problems.
Descriptors: **fault diagnosis** ; ...

...power **system** analysis **computing**
Identifiers: **neural networks** ; ...

... **fault diagnosis** ; ...

...system **engineering** ; ...

...multilayer feedforward **neural networks** ; ...

... **Radial Basis Function neural networks** ;
1995

27/3,K/38 (Item 38 from file: 2)
DIALOG(R)File 2:INSPEC

03918164 INSPEC Abstract Number: C91044611
Title: Radial basis function **networks for classifying process faults**
Author(s): Leonard, J.A.; Kramer, M.A.
Author Affiliation: Dept. of Chem. Eng., MIT, Cambridge, MA, USA
Journal: IEEE Control Systems Magazine vol.11, no.3 p.31-8
Publication Date: April 1991 Country of Publication: USA
CODEN: ISMAD7 ISSN: 0272-1708
U.S. Copyright Clearance Center Code: 0272-1708/91/0400-0031$01.00
Language: English
Subfile: C

Title: Radial basis function **networks for classifying process faults**
...Abstract: the training set, and the error function used for training. The backpropagation network has no **mechanism** in the standard training scheme for identifying regions not in any known classes. The **radial basis function** network overcomes these difficulties by using a nonmonotonic transfer function based on the Gaussian density function. While producing robust decision surfaces, the **radial basis function** also provides an **estimate** of how close a test case is to the original training data, allowing the classifier...
... the most plausible classification. For applications where this type of behavior is important, such as **fault diagnosis**, the **radial basis function** network is shown to offer clear advantages over the backpropagation network. The **radial basis function** is also faster to train because the training of the two layers is decoupled.
...Descriptors: pattern **recognition** ;
...Identifiers: pattern **recognition** ; ...

... **neural networks** ; ...

... **radial basis function** network
1991

27/3,K/39 (Item 1 from file: 6)
DIALOG(R)File 6:NTIS

1862129 NTIS Accession Number: N95-18467/7
Radial Basis Function Neural Networks **Applied to NASA Ssme Data** (Final Report)
Wheeler, K. R. ; Dhawan, A. P.
Cincinnati Univ., OH.
Corp. Source Codes: 006394000; CP730085
Sponsor: National Aeronautics and Space Administration, Washington, DC.
Report No.: NAS 1.26:195417; E-9347; NASA-CR-195417; TR-154/6/93/ECE
Jun 93 63p
Languages: English
Journal Announcement: GRAI9509; STAR3305
Order this product from NTIS by: phone at 1-800-553-NTIS (U.S. customers); (703)605-6000 (other countries); fax at (703)321-8547; and email at orders@ntis.fedworld.gov. NTIS is located at 5285 Port Royal Road, Springfield, VA, 22161, USA.
NTIS Prices: PC A04/MF A01

Radial Basis Function Neural Networks **Applied to NASA Ssme Data**
This paper presents a brief report on the application of **Radial Basis Function Neural Networks** (RBFNN) to the **prediction** of sensor values for **fault** detection and **diagnosis** of the Space Shuttle's Main **Engines** (SSME). The location of the **Radial Basis Function** (**RBF**) node centers was determined with a K-means clustering algorithm. A neighborhood operation about these...
Descriptors: *Algorithms; *Cluster analysis; *Diagnosis; *Fault detection ; *Neural nets; *Space shuttle main **engine** ; Data processing; Automatic test **equipment** ; **Engine** analyzers; Prelaunch tests

27/3,K/40 (Item 2 from file: 6)
DIALOG(R)File 6:NTIS

1850021 NTIS Accession Number: N95-14170/1
Fault **Detection and** Diagnosis **Using** Neural Network **Approaches**
Kramer, M. A.
Massachusetts Inst. of Tech., Cambridge.
Corp. Source Codes: 001450000; MJ700802
Sponsor: National Aeronautics and Space Administration, Washington, DC.
30 Oct 92 31p
Languages: English
Journal Announcement: GRAI9505; STAR3303
In Research Inst. For Computing and Information Systems, Ricis Symposium 1992: Mission and Safety Critical Systems Research and Applications 31 p.
NTIS Prices: (Order as N95-14156/0, PC A16/MF A03)

Fault **Detection and** Diagnosis **Using** Neural Network **Approaches**
Neural networks can be used to detect and identify abnormalities in real-time process data. Two basic...

... based on statistical characterization of the normal mode only. Given data representative of process faults, **radial basis function** networks can effectively identify failures. This approach is often limited by the lack of fault data, but can be facilitated by process simulation. The second approach employs elliptical and **radial basis function neural networks** and other models to learn the statistical distributions of process observables under normal conditions. Analytical models of failure modes can then be applied in combination with the **neural network** models to identify faults. Special methods can be applied to compensate for sensor failures, to produce real-time **estimation** of missing or failed sensors based on the correlations codified in the **neural network** .
...Descriptors: analysis; *Expert systems; *Failure modes; *Fault detection; *Knowledge representation; *Neural nets; *Process control (Industry); *Real **time operation** ; *Statistical distributions; Abnormalities; Correlation; Diagnosis; Education

27/3,K/48 (Item 3 from file: 34)
DIALOG(R)File 34:SciSearch(R) Cited Ref Sci

05915165 Genuine Article#: XG303 No. References: 24
Title: Neural intelligent control for a steel plant
Author(s): Bloch G (REPRINT) ; Sirou F; Eustache F; Fatrez P
Corporate Source: ESSTIN,CTR RECH AUTOMAT NANCY, CNRS, URA 821/F-54500 VANDOEUVRE LES NANCY//FRANCE/ (REPRINT); SOLLAC LIGNE GALVANIZAT ST AGATHE,/F-57191 FLORANGE//FRANCE/
Journal: IEEE TRANSACTIONS ON NEURAL NETWORKS, **1997** , V8, N4 (MAY), P 910-918
ISSN: 1045-9227 Publication date: 19970500
Publisher: IEEE-INST ELECTRICAL ELECTRONICS ENGINEERS INC, 345 E 47TH ST, NEW YORK, NY 10017-2394
Language: English Document Type: ARTICLE (ABSTRACT AVAILABLE)

, **1997**
...Abstract: Sollac hot dip galvanizing line of Florange (France) needs to integrate various approaches, including quality **monitoring** , diagnosis, control, optimization **methods** , etc. These **techniques** can be grouped under the term of intelligent control and aim to enhance the operating...

...neural models, at different levels of control. In Section II, the low-level supervision of **measurements** and operating conditions are briefly presented. The control of the coating process, highly nonlinear, is...

...two parts. In Section III, the optimal thermal cycle of alloying is determined using a **radial basis function neural network** , from a static database built up from recorded **measurements** . The learning of the weights is carried out from the results of a fuzzy C-means clustering algorithm. In Section IV, the control of the annealing furnace, the most important **equipment** , is achieved by mixing a static inverse model of the furnace based on a feedforward...

...regulation loop. Robust learning criterial are used to tackle possible outliers in the database. The **neural network** is then pruned in order to enhance the generalization capabilities.
Research Fronts: 95-1427 002 (ROBUST REGRESSION-ANALYSIS; MULTIPLE OUTLIER DETECTION; MULTIVARIATE DATA; HIGH **BREAKDOWN** POINTS)
95-0572 001 (BOUNDED-ERROR IDENTIFICATION; SIMULTANEOUS LINEAR-EQUATIONS; MUSIC ALGORITHM; GLOBAL OPTIMIZATION; PROPAGATION...

...RECONFIGURABLE FLIGHT CONTROL-SYSTEMS)
95-2621 001 (FUZZY CLUSTERING; CODEBOOK DESIGN IN VECTOR QUANTIZATION; ARTIFICIAL **NEURAL NETWORKS**)

27/3,K/76 (Item 1 from file: 99)
DIALOG(R)File 99:Wilson Appl. Sci & Tech Abs

2173042 H.W. WILSON RECORD NUMBER: BAST00052022
Diagnosis of process faults with neural networks **and principal component analysis**
Gomm, J. B; Weerasinghe, M; Williams, D
Proceedings of the Institution of Mechanical Engineers. Part E, Journal of Process Mechanical Engineering v. 214 noE2 (2000) p. 131-43
DOCUMENT TYPE: Feature Article ISSN: 0954-4089

Diagnosis of process faults with neural networks **and principal component analysis**

ABSTRACT: Industrial plants often have many **process** variable **measurements** available, which can be **monitored** for **fault** detection and **diagnosis** . Using all these variables as inputs to an artificial **neural network** for **fault diagnosis** can result in an impractically large network, with consequent long training times and high computational...

...investigated in this paper for generating a reduced number of variables to be used as **neural network** inputs for **fault diagnosis** . The main application described is to a real industrial nuclear fuel processing plant. A simulated...
...also used to assist the development of the techniques. Results in both applications demonstrate satisfactory **fault diagnosis** performance with a reduction in the number of **neural network** parameters of approximately 50 per cent using PCA. The paper also includes some introductory material on PCA and **neural networks** , and their application to process **fault diagnosis** . Reproduced by permission of the Council of the Institution of **Mechanical Engineers** .

DESCRIPTORS: ... **Radial basis function** networks...

... **Neural network** models;
2000

27/3,K/79 (Item 2 from file: 144)
DIALOG(R)File 144:Pascal

12544762 PASCAL No.: 96-0224605
Integrated diagnosis using information-gain-weighted radial basis function neural networks : **Computer aided maintenance**
YUBAO CHEN; XIAO LI; ORADY E
Dept. of Industrial and Manufacturing Systems Engineering, University of Michigan-Dearborn, Dearborn, MI 48128-1491, United States
Journal: Computers & industrial engineering, **1996** , 30 (2) 243-255
Language: English

Integrated diagnosis using information-gain-weighted radial basis function neural networks : **Computer aided maintenance**
1996
A new approach, the information-gain-weighted **radial basis function neural network** (RBFNN), has been proposed for **machinery** diagnosis in a manufacturing environment. This approach is based on the composite **neural network** , in which a series of RBFNNs are integrated together to perform the task of classification...

... gain-weighted RBFNN can produce better distinction between conditions and the scheme of a composite **neural network** is indeed an improved structure for **machinery** diagnosis in the manufacturing environment.
English Descriptors: **Measurement** ; **Fault diagnostic** ; **Artificial intellige nce^Weight f** ; Weight function; **Neural network** ; Defect detection; Experimental study; **Machining** ; Tapping

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Set     Items   Description
S1    13348477   PREDICT? OR INTUIT?? OR INTUITING OR FORECAST? OR PROGNOS?
             OR ANTICIPAT? OR EVALUAT? OR MONITOR? OR MEASUR?
S2    11915206   APPROXIMATING OR CALCULAT? OR COMPUTING OR COMPUTE OR COMP-
             UTES OR COMPUTED OR ESTIMAT? OR APPRAIS? OR ASSESS? OR TREND?-
             (3N)ANALY? OR INTERPOLAT? OR RECOGNI? OR EXTRAPOLAT? OR DERIV?
S3     3055730   S1:S2(7N)(METHOD? OR SYSTEM? OR PROCESS?? OR PROCEDUR? OR -
             TECHNIQUE? OR MODE?)
S4     1879896   (REMAINING? OR REMAINDER? OR AVAILAB? OR LEFT OR RESIDUAL?-
             )(5N)(LIFE? OR YEAR? OR TIME? OR DAY OR DAYS OR HOUR? OR WEEK?
              OR MONTH?)
S5      804979   TIME(2W)FAILURE? OR FAULT?(2W)DIAGNOS? OR TIME(2W)OPERATIO-
             N? OR (WORK? OR OPERATION?)(2N)LIFE? OR BREAKDOWN? OR (BREAK?
             OR BROKE?)()DOWN
S6        2907   (VIRTUAL? OR THEORETIC?)(2N)(AGE OR AGES OR AGING)
S7    17524368   MACHIN? OR EQUIPMENT? OR APPLIANC? OR APPARATUS? OR TOOL? ?
              OR ENGINE? OR INDUSTR?()DEVICE? OR MECHANIC? OR MECHANISM?
S8       79654   S1:S3(10N)S4:S6 AND S7
S9      207668   NEURAL()NETWORK? OR MACHINE()(LEARN? OR INTELLIGEN?) OR AR-
             TIFICIAL()INTELLIGEN? OR AI OR GAUSSIAN? OR FUZZY()(LOGIC? OR
             INFERENC? OR THEOR?)
S10       2609   RADIAL()BASIS OR BASIS()FUNCTION? OR RBF OR RADIALBASIS? OR
              BASISFUNCTION? OR RBFN
S11         28   S8 AND S9 AND S10
S12        164   S8 AND S6
S13         38   S12 AND S9:S10
S14         66   S11 OR S13
S15         47   S14 AND PY<2001
S16         28   RD (unique items)
File   9:Business & Industry(R) Jul/1994-2005/Aug 04
         (c) 2005  The Gale Group
File  13:BAMP 2005/Jul W4
         (c) 2005  The Gale Group
File  15:ABI/Inform(R) 1971-2005/Aug 05
         (c) 2005 ProQuest Info&Learning
File  16:Gale Group PROMT(R) 1990-2005/Aug 04
         (c) 2005 The Gale Group
File  88:Gale Group Business A.R.T.S. 1976-2005/Aug 04
         (c) 2005 The Gale Group
File  98:General Sci Abs/Full-Text 1984-2004/Dec
         (c) 2005 The HW Wilson Co.
File 148:Gale Group Trade & Industry DB 1976-2005/Aug 05
         (c)2005 The Gale Group
File 160:Gale Group PROMT(R) 1972-1989
         (c) 1999 The Gale Group
File 275:Gale Group Computer DB(TM) 1983-2005/Aug 05
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         (c) 2005 Reed Business Information Ltd.
File 370:Science 1996-1999/Jul W3
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File 484:Periodical Abs Plustext 1986-2005/Jul W5
         (c) 2005 ProQuest
File 553:Wilson Bus. Abs. FullText 1982-2004/Dec
         (c) 2005 The HW Wilson Co
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File 621:Gale Group New Prod.Annou.(R) 1985-2005/Aug 05
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File 636:Gale Group Newsletter DB(TM) 1987-2005/Aug 04
        (c) 2005 The Gale Group
File 647:CMP  Computer Fulltext 1988-2005/Jul W3
        (c) 2005 CMP Media, LLC
File 674:Computer News Fulltext 1989-2005/Jul W5
        (c) 2005 IDG Communications
File 696:DIALOG Telecom. Newsletters 1995-2005/Aug 04
        (c) 2005 Dialog
File 810:Business Wire 1986-1999/Feb 28
        (c) 1999 Business Wire
File 813:PR Newswire 1987-1999/Apr 30
        (c) 1999 PR Newswire Association Inc
?
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16/3,K/14 (Item 1 from file: 148)
DIALOG(R)File 148:Gale Group Trade & Industry DB

11763764 SUPPLIER NUMBER: 57485725 (USE FORMAT 7 OR 9 FOR FULL TEXT)
Hydrocarbon Processing's Advanced Control and Information Systems '99.(innovations in control hardware and software packages)
Hydrocarbon Processing, 78, 9, 75(7)
Sept, 1999
ISSN: 0018-8190 LANGUAGE: English RECORD TYPE: Fulltext
WORD COUNT: 60179 LINE COUNT: 05469

... explicitly as dependent variables. A dynamic process model is developed using the DMCplus model identification **tool** . Its controller/sub-controller structure enables full-scope benefits to be captured through the application...using first principles models, or Honeywell's soft sensor toolkit utilizing state-of-the-art **neural network** technology.
Inventory control adjusts the i(C.sub.4) make-up rate to control the ...

...multiple process models and an integrated real-time macro programming environment in addition to nonlinear **RBF** models and **fuzzy logic** capabilities.
Connoisseur is applied to improve control of total feed composition and operating conditions to...the same model for rigorous process simulation as well as online optimization. An offline process **engineering** analysis **tool** is produced directly from the implementation of the optimization system. This offline **tool** allows users to examine "what-if" scenarios, using a rigorous model which has been auto...

...online optimization system is designed to meet multiple objectives. These include maximizing plant profitability, plant **equipment** performance monitoring, plant instrument monitoring and providing information on intermediate plant streams. Specific functions provided...

...overall plant economics
* Optimal process operation through closed-loop execution
* Improved ability to check on **equipment** performance parameters.

Economics. Increase in profit of between $0.10 and $0.20 per barrel ...

...avoid upsets that convey corrosive HF acid (the catalyst) into undesired areas of the process **equipment** . The advanced controls include the following strategies that can be implemented via advanced regulatory techniques...
...feed contamination
* Monitor alkylate production and advise how to push production against current constraints
* Monitor **equipment** such as pumps, compressors, condensers and exchangers for changes that could indicate potential problems which could affect the process or lead to **equipment** failure (e.g., pump cavitation, exchanger fouling, exchanger cross leaks, finfan failure, etc.)
* Identify potential...amine concentrations, water content, loadings and salts to maintain optimal concentrations and maximize utilization
* Monitor **equipment** such as pumps and exchangers for changes that could indicate potential problems which could affect the process or lead to **equipment** failure (e.g., pump cavitation, exchanger fouling, exchanger cross leaks, fin fan failure, etc.)

* Identify...buffers during process upsets, resulting in minimized downward feed adjustments during plant upsets caused by **mechanical** failure or other process problems.

MVC is a proven nonlinear multivariable control and economic optimization...

...and product shipments. The module enables a scheduler to rapidly respond to events such as **equipment** outages, and supply and distribution changes, all while maintaining a robust, feasible and profitable schedule...the user to create blend orders directly from displays or download them from a planning **tool** . Blend orders are available for viewing, monitoring and reporting from the time they are first...

...far into history as the client desires.

Control strategy. The ABC considers property, inventory and **equipment** constraints for the current blend and blends running on other blend headers. The ABC maintains...

...a nonlinear optimizer that finds the optimum recipe to meet the property targets, inventory and **equipment** constraints while maximizing the economic objective. The user can select the objective to maximize profit... with DMCplus with feedback from a measured or inferred octane, while respecting the critical hydraulic, **mechanical** and catalyst deactivation limits. A single controller addresses the interaction of severity and coke laydown...

...the Aspen Catref rigorous kinetic model of the reactors with catalyst deactivation and associated process **equipment** to calculate optimum targets for maximizing unit or complex profitability. The scope can range from...CCR)

* Identify leaking valves in the CCR; identify lock hopper problems, causes and remedies
* Monitor **equipment** such as pumps, compressors, condensers and exchangers for changes that could indicate potential problems that could affect the process or lead to **equipment** failure (e.g., pump cavitation, exchanger fouling, exchanger cross leaks, finfan failure, etc.)
* Identify potential...to simultaneously manipulate the controller targets to maintain smooth operation and constant furnace yields within **equipment** constraints. A rigorous optimization layer based on MDC Technology's RTO+ product is an option...plant. Advanced control stabilizes the furnace effluent rate and composition and operates closer to actual **equipment** constraints, often yielding benefits over $1 million per year. Real-time optimization benefits can often...

...Technology's Quality Controller for CDUs uses the column cutpoints as its primary underlying control **mechanism** , as opposed to product draw-offs, which are used by most other systems. This uses...

...uses Crude Switch Property Predictor technology.

Strategy. The Crude Switch technology applies first principles and **neural network** models to compute first the column heat balance, and second the product properties. This is...
...of upsets, and quick prediction of product quality deviations. Further, first principles models, enhanced by **neural network** models, have a wide range of validity and do not necessitate frequent calibration.

Advantages of...

...Property Predictor over earlier versions are:

* It is implemented as a parameterization of a commercial **neural network** software package

* It will cascade to any pre-existing MVC application
* It uses the entire...optimization of the crude and vacuum unit with Aspen RT-Opt uses rigorous, open-equation **engineering** models of the complete unit including the preheat system, heaters, light-ends columns and naphtha...

...feed composition, heat transfer coefficients, furnace efficiencies, etc. The model is also used offline for **engineering** studies, feedstock selection or Aspen Plus design studies, and to update planning and scheduling models...

...fractionator yields and cutpoint targets and advise how to push production against current constraints

* Monitor **equipment** such as pumps, compressors, condensers and exchangers for changes that could indicate potential problems which could affect the process or lead to **equipment** failure (e.g., pump cavitation, exchanger fouling, exchanger cross leaks, fin fan failure, etc.).
* Identify...

...constraint limit - for example, maximum feed - by looking at the operation of upstream and downstream **equipment** .

Economics. Benefits of Expert System Process Advisors include:

* Better unit monitoring for safer operation and deploying various software **tools** including process historians, databases and spreadsheets, first principles simulation and LP models in an automated...

...from HYSYS. Comparisons between measured and calculated results are then automatically made to flag potential **equipment** deficiencies. Additionally, simulated results provide information about the plant that is not or cannot be measured such as rotating **equipment** efficiencies, column flooding percentages, Rvp, calculations, etc. Excel automatically generates tables and graphs based on the measured and simulated data to track **equipment** performance and highlight anomalies. Normally, the entire process is executed about once an hour. The...

...crude unit and is scheduled to be implemented on an FCC unit.

Licensor. AEA Technology **Engineering** Software, Hyprotech Ltd., Calgary, Alberta; Houston, Texas.

Cryogenic separation

Application. Cryogenic recovery is used to...

...to achieve the control objective and economic benefits: (1) maximize chiller duty without violating the **equipment** process constraints (chiller duty is the manipulated variable subject to constraints of maximum chiller level...

...a series of catalytic fixed bed reactors. Accounting for all process interactions, hydraulic limits and **equipment** constraints is particularly important in order to reduce operating costs. Implementing DMCplus multivariable constrained control...proprietary model developed for process design and adapted for online control.

* The inferential control uses **neural network** intelligent regression technology to predict product qualities in the fractionator based on flows, temperatures and...

...sensor package. The flexible client/server allows the user to "plug in"a variety of **engines** (empirical, rigorous, **fuzzy logic** , neural net, custom, etc.) to generate the online models. Analyzer validation and update as well...or can be developed using Honeywell's soft sensor toolkit, a state-of-the-art **neural network** technology for developing inferential

models.
Fractionator toolkit technology provides a standard, user-friendly collection of...

...action for the specific process condition.
* At each execution, information is available for operators and **engineers** to understand controller actions, active constraints and process predictions. More specific advisory systems can also be customized.
* While the controller uses its own dynamic models, **neural network** -based inferential predictions for drum outage and product properties have also been integrated seamlessly.
Economics...of light ends in the stripper under certain combinations of temperatures, pressures and flows)
* Monitor **equipment** such as pumps, compressors, condensers and exchangers for changes that could indicate potential problems which could affect the process or lead to **equipment** failure (e.g., pump cavitation, exchanger fouling, exchanger cross leaks, finfan failure, etc.)
* Identify potential...

...chemicals/petrochemicals)
Application. Enterprise optimization enables optimizing and integrating the extended supply chain, manufacturing and **engineering** to increase business performance and reduce costs.
Strategy. Aspen Technology's Enterprise Optimization is achieved... Aspen Plantelligence suite can be leveraged in the areas of plant optimization, production management and **engineering** . Business processes typically involved in manufacturing optimization include planning, scheduling, process control, online optimization, operator...

...business processes through faster access to accurate information pertaining to the supply chain, manufacturing and **engineering** facets of the business are substantial, and often add up to tens of millions of...

...and information to manage and optimize each facet of the business enables integrating and re- **engineering** business processes to improve profitability.
Commercial installations. Within the chemical and petrochemical industries, AspenTech has...

...optimization (polymers)
Application. Enterprise optimization enables optimizing and integrating the extended supply chain, manufacturing and **engineering** to increase business performance, reduce costs and help achieve six sigma quality control.
Strategy. Aspen...

...Aspen Plantelligence suite can be leveraged in the areas of plant optimization, production management and **engineering** . Business processes typically involved in manufacturing optimization include planning, scheduling, process control, conformance monitoring, recipe...

...business processes through faster access to accurate information pertaining to the supply chain, manufacturing and **engineering** facets of the business are substantial, and often add up to tens of millions of...

...and information to manage and optimize each facet of the business enables integrating and re- **engineering** of business processes to improve profitability, enhance customer satisfaction and move toward six sigma quality...

...refining)

Application. Refining enterprise optimization enables optimizing and integrating the extended supply chain, manufacturing and **engineering** to increase business performance and reduce costs for refiners and gas processors.

Strategy. Aspen Technology...

...suite can be leveraged in the areas of plant optimization and control, production management and **engineering** . It is based on a continuous improvement "design-operate-manage" paradigm and enables customers to... business processes through faster access to accurate information pertaining to the supply chain, manufacturing and **engineering** facets of the business are substantial, and often add up to tens of millions of...

...and information to manage and optimize each facet of the business enables integrating and re- **engineering** business processes to improve profitability.

Commercial installations. A number of clients have Refining Enterprise Optimization...

...data from lab systems, material movement and storage, advanced control, process optimization and process control **equipment** and make it available to ERP systems.

Effective integration of ERP and plant systems is...

...of analysis for finished products

* Plant maintenance: integrating asset management and IM systems enables identifying **equipment** in need of repair/recalibration and automatic work order generation in the maintenance system.

Economics...added and removed from the regenerator

* Policies for adjusting atomizing, stripping and riser steam

* Monitor **equipment** such as pumps, compressors, condensers and exchangers for changes that could indicate potential problems that could affect the process or lead to **equipment** failure (e.g., pump cavitation, exchanger fouling, exchanger cross leaks, finfan failure, etc.)

* Identify potential...are downloaded to DMCplus for implementation. Refinery planners can use the highly accurate yield and **equipment** constraint data from the online optimizer to improve the refinery LP planning models.

Economics. Benefits...

...operating severity); extensive literature and patent search for FCC/ROC/DCC reactor catalytic and kinetics **mechanism** , design and operation; technical staffs operating expertise and market forces psychology as the knowledge base. The latest economic, kinetics theory, **artificial intelligence** , **fuzzy logic** , neural net and chaos theory-based expert systems have been applied. These systems simulate global...

...objectives

* Policies for adjusting stripping steam rates depending on the type of crude run

* Monitor **equipment** such as pumps, compressors, condensers and exchangers for changes that could indicate potential problems which could affect the process or lead to **equipment** failure (e.g., pump cavitation, exchanger fouling, exchanger cross leaks, finfan failure, etc.)

* Identify potential...targets are implemented with feed-forward compensation for inlet disturbances and with limit checks for **equipment** constraints. Excess oxygen can be controlled in each firebox when proper instrumentation is available.

Inferential...

...multiple process models and an integrated real-time macro programming environment in addition to nonlinear **RBF** models and **fuzzy logic** capabilities. ROMeo is SIMSCI's Rigorous Online Modeling and Equation-based Optimization software providing a...optimum operating targets for the Connoisseur controller. Typical objectives are:

* Maximizing unit throughput up to **equipment** constraints
* Maintaining product quality while maximizing yield of most valuable products
* Maximizing preheat train, pumparound...

...then optimizes unit performance using variables, constraints and profit objectives defined by plant managers, process **engineers** and/or unit operators. ROMeo rigorously calculates and returns new operating setpoints to achieve the...

...or can be developed using Honeywell's soft sensor toolkit, a state-of-the-art **neural network** technology for developing inferential models. Controlled variables may include:

* Naphtha 95% pt.
* Heavy naphtha 95...

...and correspond with the ASTM measurements made by the plant lab. The desired properties are **calculated** online from commonly **available real-time process measurements** . The **calculated** boiling properties are then used to control products to specification by manipulating draw rates and...similarity of most light product fractionators, considerable variation occurs in operating objectives and in auxiliary **equipment** such as reboilers and coolers. Advanced control strategies should be tailored accordingly.

Strategy. A number...

...The purposes of a fuel gas Expert System Process Advisor application are to provide the **tools** and advice for overall fuel gas system optimization. Gensym's G2 is used to store...fractionator yields and cutpoint targets and advise how to push production against current constraints

* Monitor **equipment** such as pumps, compressors, condensers and exchangers for changes that could indicate potential problems which could affect the process or lead to **equipment** failure (e.g., pump cavitation, exchanger fouling, exchanger cross leaks, fin fan failure, etc.).

The...

...constraint limit - for example, maximum feed - by looking at the operation of upstream and downstream **equipment** .

Economics. Benefits of Expert System Process Advisors include:

* Better unit monitoring for safer operation and...

...Texas.

Hydrocracker/hydrotreater

Application. This advanced control and optimization package provides refineries with the necessary **tool** to maximize their profits during seasonal market variations by easily adjusting the gasoline/distillate production...widely different feedstocks and operating conditions. These reactor models can easily be connected to other **equipment** models, e.g., rigorous fractionation, to create a fully integrated model of the entire hydrotreater...

...achieved by linking the optimization systems to other rigorous models and to off line planning **tools** such as Aspen PIMS.

Commercial installations. AspenTech has commissioned 27 hydrocracker and 13 hydrotreater advanced...

...and loads, operating severity); extensive literature and patent search for hydrocracking reactor catalytic and kinetics **mechanism** , design and operations; technical staffs operating expertise and market forces psychology as the knowledge base. The latest economic, kinetics theory, **artificial intelligence** , **fuzzy logic** , neural net and chaos theory-based expert systems are applied. These systems simulate global central...costs, particularly when there are large differences in feed prices and qualities and when feed **availabilities** vary with **time** . As a rough **estimate** , the package would achieve an increase of 5-10% of the cheapest feed and a...

...combustion controllers combine to reduce furnace energy consumption by 5-10%. The smooth operation increases **equipment** life and furnace safety. Long periods of hydrogen over-production are virtually eliminated.

Commercial installations...

...The purposes of a hydrogen system Expert System Process Advisor application are to provide the **tools** and advice for overall hydrogen system optimization. Gensym's G2 is used to store the...quality models are developed using Honeywell's soft sensor toolkit, a state-of-the-art **neural network** technology for developing inferential models.

Intermediate regulatory controls are supplied using standards packages to providesafety, **engineering** , operational, economic and more.

In combination with Resolution's Target-Setting solution, one installation reported...

...DMCplus controllers obtain these benefits by continuously pushing the unit and operating it simultaneously at **equipment** and process constraints. Optimization system benefits are obtained by determining the most profitable set of...

...model utilizes rigorous kinetic models of the reactors, dehydrogenation catalyst deactivation and the associated process **equipment** to calculate the optimum targets for maximizing profitability. Dehydrogenation reactor catalyst deactivation provides many optimization...

...on the GMAXC multivariable predictive controller to maximize quality and economic goals while honoring safety/ **equipment** limits.

Strategy. The primary control strategies are:

* Product qualities: Maintain LPG product quality in terms...

...maximization: Maximize butane recovery from the feed gas

* Feed throughput: Maximize feed rate subject to **equipment** limits, quality specifications and inlet feed.

In addition to analyzer measurements, other variables like tower...

...for containing the process in case the analyzer indicators are not accurate or timely.

For **equipment** constraints, compressor speed, expander valve position and debutanizer delta pressure are also added to the...
Application. Resolution's Offsite Data Management is built within the REPOSITORY database. This solution provides **tools** for reviewing and changing tank compositions, consolidated inventory reporting by area and stock category, movement...

...enable the movements' automation system to remain current with the actual configuration of the field **equipment** . OMIS also provides a relational database for reporting, storage of report transactional information and for connection to multiperiod planning **tools** and schedulers.

Economics. Economic benefits include greater utilization of tank ullage, spill and loss prevention, reduced demurrage charges due to improved utilization of capital **equipment** and opportunities to maintain a wider variety of product as required by market demands, or...automated movements resulting in reduced tanker demurrage. The following are typical benefits sources:

* More efficient **equipment** utilization (faster job turnaround)
* Decreased blender product quality giveaway and blending costs
* Reduced oil losses...

...functions, such as maximum profit at fixed or unlimited production. Rigorous models for all major **equipment** are included.

The advanced process control system includes production controller, model-based furnace severity control...Distillation column pressures and product purities.

Constraint variables are typically designed to represent:

* Process and **equipment** performance limitations (i.e., furnace tube metal temperatures, compressor speed and driver horsepower, and distillation...

...are implemented using the STAR multivariable predictive controller.

Optimization strategy. NOVA consists of a solution **engine** for nonlinear optimization and equation solving problems, a library of equation-based unit operations models...

...limits for STAR multivariable predictive controllers that run every 1-3 minutes to ensure that **equipment** constraints are honored as the optimization results are implemented in the plant.

STAR multivariable predictive...

...capacity, optimization of yields and feedstock selection, and to provide valuable information to operators and **engineers** to operate the plant at optimum conditions. Model-based advanced control enforces the optimum setpoints...is complex, and it is impossible for the operator to deduce the optimum without modeling **tools**

* The process is subject to constant change
* There are many degrees of freedom.

The overall...

...and plant operators' expertise and market psychology. The latest neoclassic economy, thermodynamic and kinetic theories, **fuzzy logic**, **neural network** and chaos theory have been applied to develop expert system-based decision simulators. Monetary policy...plantwide constraint control LPs. The model combines rigorous kinetic models with thermodynamic property models and **equipment** models. This model is also periodically parameterized or updated using data from the plant. This...

...and distributed to automation systems for execution.

The SAND module is a supply chain optimization **tool** that determines the optimal method of producing products and satisfying customer demand with multiple manufacturing...

...oils selected for processing and for preparing production plans.

The RPMS module is a planning **tool** that supports evaluating and selecting raw materials, formulating optimal production plans, evaluating capital investments and...

...by RPMS or an equivalent appenables a scheduler to rapidly respond to events such as **equipment** outages, and supply and distribution changes, all while maintaining a robust, feasible and profitable schedule...as part

of the refinery operations. Taking advantage of the sequential and rules-based modeling **tools** minimizes base oil production cost. Extending the planning model to an AspenTech sequencing model results...

...Results from the short-term plan are fed to the AspenTech refinery scheduler for tactical **equipment** scheduling and inventory projections.
Lube plant planning establishes the demands for raw materials and inventory...

...Massachusetts, and Houston, Texas.
Planning and scheduling (refining)
Application. Aspen Technology's planning and scheduling **tools** are unique in their capability to provide accurate production targets by integrating plantwide optimization with process simulation and optimized event modeling. This suite of **tools** consists of Aspen PIMS, PIMS-SX and REF-SKED.
Strategy. Aspen PIMS planning and scheduling...

...planning and scheduling.
Aspen PIMS is a powerful yet easy-to-use family of productivity **tools** for economic planning in the process industries. It offers all the advantages of cost, accessibility...a solid foundation on which to apply ASM advanced technology solutions. The necessity of these **tools** and the overall alarm management improvement process is driven by the often less-than-disciplined...

...settings. This information is useful in rationalizing the alarm system, for on-going alarm system **engineering** , and can be provided to assist operators in responding to an alarm.
* The Alarm Rationalization...

...This can speed root-cause analysis and identify relations among various alarms.
Strategy. Apply these **tools** in a coordinated manner to assess performance of an alarm system, identify problems and improve...

...a reasonable time frame. To complicate matters further, alarm strategies are usually installed, rather than **engineered** . Consequently, many nuisance alarms constantly interfere with daily operator activities. Operators can easily separate important...

...alarms, and organize the visual format of incoming data to suit their needs. The analysis **tools** can detect redundant and predictable alarms, possibly eliminating over half of the alarms altogether.
Strategy...

...and incorrect limit alarms.
* Find predictable alarms: Find the alarms that are predictable using statistical **tools** .
* Cause-and-effect analysis: Which alarms showed the root-cause of the upset?
Economics. An...operation can be readily identified.
This factual presentation challenges operators, managers, laboratory, control and process **engineers** to provide reasons and explanations. In rising to these challenges much new insight and process...

...explored. The very ergonomic display controls provided by CVE lead to a considerable rise in **engineer** productivity whether measured by the increase in analysis achieved in a given time, or the additional benefits achieved from the use of the **engineer** 's time.

Users have identified 11 key benefit areas.
* Setting efficient operating guidelines and better...

...the process units. Sensor elements are then configured into their required relationships to the process **equipment** to detect abnormal operation scenarios before they escalate into major incidents. Failure analysis is based...

...of their performances based on material and energy balance models configured from a library of **equipment** objects. As a failure is diagnosed, a message will be propagated to the operator on...
...developing production and reliability management applications. ASM4G2 integrates browsers and ActiveX components to support multiple **neural networks** , control systems, operating systems and databases. ASM4G2 also supports the client's legacy and third...

...Reliability management applications integrate dynamic sensor data from vibration analysis systems with ASM4G2 to include **equipment** health logic in the operations diagnostics.

Production management applications. The rules and procedural-based reasoning...

...ASM4G2 software to provide dynamic advisories to operators as abnormal situations are detected. The knowledge **engineering** interviewing process yields additional process management rules beyond the standard operational procedures.

Benefits. Typical savings...

...but are not fully appreciated until the site experiences a major production outage due to **equipment** failure that should have been predicted.

Commercial Installations. Petrochemicals - four sites; Refining - two sites, 25 units; pulp and paper - one site.

Licensor. Nexus **Engineering** , Kingwood, Texas.

Plant information (asset management)

Application. The @sset.MAX Alert Manager is an advanced...integrates information from a variety of sources to detect long-term changes in performance and **mechanical** behavior. All sub-systems are monitored to provide early and specific warnings and reduce unnecessary...

...and notifications occur automatically, without human intervention. Actionable information is presented to operating, maintenance and **engineering** staff. Collaboration with world-class experts, system manufacturers and internal staff is facilitated to assist...

...can have large financial and environmental impacts. Lost production, flaring and incremental damage to the **machine** may occur with each shutdown. When a large asset fails, a significant process event or...

...a complete package for representing what actually happens in a process plant for both process **engineers** and yield accountants. It combines:
* A state-of-the-art process flow diagram interface
* A...

...measurements and produces a single consistent set of the most accurate reconciled data possible. Accounting, **engineering** , planning/scheduling, maintenance and management use this data toward a goal of more profitable operations...

...of operating tips/art/techniques for planning an optimized transition.

Objectives.
* Provide intelligent support to **engineers** for planning transitions
* Provide seamless access to data from multiple sources, including real-time plant...A computer with a Pentium processor running Microsoft NT Server 4.0 supplies the human- **machine** interface (HMI) to the MVC/Database system with data collection, trending and data retrieval abilities... technology into finance, cost accounting, human resources, feedstock, fuels procurement, inventory, plant daily operating information, **equipment** and instrumentation/DCS maintenance, emergency shutdown, startup and explosion accident information systems support and information...

...information.
* Process plant operating DCS management process startup, emergency shutdown, troubleshooting, waste minimization energy conservation, **equipment** design and maintenance information.

Operations management implementation. OSA consultant will conduct the corporate/plant operations...
...standard products already exist.

Benefits. RESOLUTION provides for integration of ALL plant data: operational, economic, **engineering** , planning, maintenance, documentation and more. This both provides "one stop" shopping for data, and eliminates ...

...drastically reduced hence, greatly reducing costs.

RESOLUTION is designed with integration in mind: its RELAYER **tools** for third-party system integration greatly reduce the cost of an integrated system integration project...view all data.

Economics. ProcessNet exposes highly valuable process data and reports to operators and **engineers** who use it for improved productivity, higher profits and better flexibility. In addition, ProcessNet effectively ...

...modeling, can lead to avoiding substantial capita) expenditures.
* Personnel productivity: Availability of sound decision support **tools** , reports and process analysis **tools** has resulted in significant, audited improvements in operating staff productivity.
* Regulatory compliance: Information management systems...

...historian to manage all types of plant information; an integrated plant reference model; and desktop **tools** to display, analyze, report on and navigate through plant data. The unified database approach allows for managing plant data as diverse as continuous process data, discrete events, **equipment** records, product specifications and shipment records. More than an historian, the embedded plant reference model...

...the infrastructure for the industrial desktop, a development environment that fosters integration using standard Microsoft **tools** such as ... Microsoft's dominance in the market creates a de facto standard for integrating refinery software. **Tools** such as ActiveX controls and ODBC coupled with the VBA development environment eliminate the need...

...information integration to maintenance asset management minimizes unnecessary maintenance procedures and inventories, while ensuring plant **equipment** and personnel availability. Automated business reporting driven from production systems allows up-to-the-minute...

...are accurately translated into production targets and properly communicated. The Business.FLEX planning and scheduling **tools** , and Honeywell's advanced control system can be integrated to streamline the process of translating plans into production.

Operations Monitoring compares operating targets to actual results, and provides **tools** for explaining and analyzing the differences. Operations Monitoring helps reduce production variability and cost, and... and emergency operations); management and plant operators' expertise. The latest statistical, thermodynamic and kinetic theories, **artificial intelligence** in **fuzzy logic** , **neural network** and chaos theory have been applied to develop expert system-based decision simulators covering the...

...and minimization

* Maximize product recovery while minimize off-spec loss
* Process plant quality assurance and **equipment** preventive safety and maintenance management
* Process plant technical, operating and DCS staff on-the-job...

benefits include:

* More stable operation
* Less operator interaction
* Improved process safety
* Better utilization of process **equipment** .

Tangible benefits include:

* Increased revenues
* Decreased operating costs
* Reduced occurences of off-specification penalties.

Experience...Sitewide networks for plant data acquisition and distribution

* Sitewide LP modeling
* Unit simulation and optimization
* **Equipment** performance monitoring
* Advanced process control, including model-based techniques
* Process alarm management.

Implementation. Computer systems...with modern higher-level business systems.

Cost Management - Provides calculation of production costs by major **equipment** , major unit and mode of operation. Actual results are calculated against a plan. Performance indices...

...different plants continuously.

Intelligent Performance Monitoring - Supports rigorous performance monitoring of individual units and major **equipment** . Both long-term trends and sudden changes in performance can be detected. This helps identify likely candidate **equipment** for preventive maintenance.

Quality Management - Laboratory data are associated with the batch or lot produced...

...of production. This facilitates problem solving and data retrieval for reporting purposes.

Process Analysis - Provides **tools** for advanced statistical analysis and trending of process and laboratory data. This provides operations, technical...

...FORWARD C is an interactive system dedicated to scheduling refinery operations. It provides a single **tool** to solve all refinery scheduling problems from crude arrivals to finished product delivery.

Strategy. FORWARD C combines the experience of the scheduling team and the power of object-oriented programming, **artificial intelligence** , constraint propagation, linear programming, simulation and efficient user interface techniques to solve refinery scheduling problems...

...sales gas flow, CV, etc.).

* The gas separation plant, which represents the stream routing, separation **equipment** and process constraints. The model may be targeted to achieve one ...the APCS calculations are highly interactive and interdependent. Most of these equations are based on **engineering** principles, rather than regressions or curve fits of plant operating data.

The controls are very...

...range of current values, trends and accumulative information of benefit to operations, management, accounting and **engineering** personnel.

Economics. APCS will typically have a payback of six months to two years, depending...

...The online models combine information from plant data (operation) and physical models (knowledge) into a **neural network** . Model predictive control and continuous optimization are nonlinear, important in this process where gains can...index, density, flow index, stress exponent and MFR are inferred using an Aspen IQ hybrid **neural network** -based virtual analyzer. Inferential properties are developed by modeling real-time data and using predictive...

...a nonlinear dynamic process model into a single optimization problem. Dot Products' large scale optimization **engine** , NOVA, is then used to solve for the appropriate control action. The control that can...

...the APCS calculations are highly interactive and interdependent. Most of these equations are based on **engineering** principles, rather than regressions or curve fits of plant operating data.

The controls are very...range of current values, trends and accumulative information of benefit to operations, management, accounting and **engineering** personnel.

Economics. Better steady-state operation due to the APCS yields 0-20% improvement in...

...The online models combine information from plant data (operation) and physical models (knowledge) into a **neural network** . Model predictive control and continuous optimization are nonlinear, important in this process where gains can...

...model for immediate comparison of actual vs. planned performance.

As a stand-alone production accounting **tool** , Aspen Advisor provides much more capability than traditional in-house custom spreadsheets. The system combines...constraint-handling capabilities.

The Aspen RT-Opt rigorous modeling and optimization system provides a superior **tool** for real-time process simulation. Aspen RT-Opt determines in real-time the optimum operating...number of plant areas are subject to performance degradation, online performance monitoring is an important **tool** to maximize plant utilization. The key areas for performance monitoring are:

* Furnace thermal efficiency
* Catalyst...

...problem from hydrocarbons being carried over in the rich amine or sour water streams.

* Monitor **equipment** such as pumps, compressors, condensers and exchangers for changes that could indicate potential problems, which would affect the process or could lead to **equipment** failure (e.g., pump cavitation, exchanger fouling, exchanger cross leaks, finfan failure, etc.).
* Identify potential...

...Park, California, and Katy, Texas.
Supply chain technology (refining)
Application. Aspen Technology's supply chain **tools** , together with the other Enterprise Optimization technologies, enable dynamic and holistic management of a demand...

...moving the supply chain management on to a demand-driven basis - AspenTech's supply chain **tools** , together with the other Enterprise Optimization technologies, enable dynamic and holistic management of a demand...the enterprise to manage and optimise each facet of the business enables integrating and re- **engineering** business processes to permit accurate implementation and realization of the optimal supply chain plans, thereby...
...applications. Linear and nonlinear computational tasks include at least the following: alarm or limit checking; **equipment** performance (efficiency) calculations; capacity calculation for boilers; steam surplus calculation; electric surplus calculation; peak demand...

...buy" advisory calculations; fuel selection; report generation; alarm logging and display; and display formatting. Process, **equipment** and environmental constraints are honored continuously and may be weighted in importance or value according...

...heat and electrical power.
Factors such as ambient air conditions, electricity prices, process demands and **equipment** degradation can greatly affect the optimal operating points.
Tightening environmental limits on N(O.sub...

...optimum, and a case with "day zero" or clean parameters to evaluate the cost of **equipment** degradation.
The plant optimization application uses MDC Technology's advanced optimization system, incorporating a variety...

...operator. Total plant optimization is achieved by employing a tiered system:
* Continuous optimization allows current **equipment** to operate at minimum cost for a given demand and within the emissions and **equipment** constraints.
* Configuration optimization performs the optimal **equipment** selection with current **equipment** performance and penalties to prevent excessive **equipment** starting and stopping.
* Look-ahead optimization predicts future plant operation based on profiled demands/prices...

...demand for new process plants.
Strategy. Visual MESA is an online, graphical steam system management **tool** that can solve the problems described above.
* Visual MESA protects your steam system by monitoring...

...minimum operating cost using optimization. Visual MESA also optimizes starting and stopping of individual spared **equipment** , like turning on a motor and turning off a turbine. Optimization is customized to your...

...can be achieved simultaneously by OSA-based reactors yield and fractionation system operations improvement.
These **artificial intelligence** expert system-based integrated system rigorous models have been developed out of the entire operating...

...and debottlenecking

* Process startup, emergency shutdown and troubleshooting simulations, and energy minimization
* Process plant energy **equipment** preventive safety and maintenance
* Maximum product recovery at minimum energy and waste pollution
* Process utility...

...50% energy saved or millions of U. S. dollars saved in energy costs annually without **equipment** hardware investment

Commercial installations. Two refinery, three olefins, two caprolactam, two styrene, two polyolefin, 12...Application. Steam System Program (SSP) is a general steam balance package that allows the utility **engineer** to easily add, delete and modify **equipment** models as needed to accurately reflect and optimize current utility system operations.

Strategy. SSP provides convenient modeling and optimization of plantwide utility systems. Preprogrammed **equipment** modules are included, such as boilers, gas turbines, steam turbines, cogen units, electric drives, generators...

...steam systems. Thermodynamic properties of steam and water are automatically calculated for use in the **equipment** models. Plant operating costs are computed based on electrical generation and consumption and the required...

...be used offline in a case study manner to study potential operating modes or future **equipment** changes.

Economics. Typical savings range from $50 to $400/hr depending on plant size and...

...doing. The purposes of a steam system Expert System Process Advisor are to provide the **tools** and advice for overall steam system optimization. Gensym's G2 is used to store the...setpoint ramping functions, help to reduce process upsets as well as relieve operator excessive attention. **Engineering** calculations improve process monitoring and safety, e.g., calculating and displaying reactor explosive limits and...

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Set     Items   Description
S1        398   AU=(DARKEN C? OR DARKEN, C? OR LOECHER M? OR LOECHER, M? OR
                  LOCHER M? OR LOCHER, M?)
S2          9   CHRIS?(2N)DARKEN OR MARK?(2N)(LOCHER OR LOECHER)
S3     678322   NEURAL()NETWORK? OR VIRTUAL()AGE OR RADIAL()BIAS OR RBF OR
                 BIAS()FUNCTION? OR WEAR?()INCREMENT? OR ARTIFICIAL()INTELLIG?
                 OR AI OR MACHINE?()LEARN?
S4         23   S1:S2 AND S3
S5         11   RD (unique items)
? show files
File   2:INSPEC 1969-2005/Jul W4
         (c) 2005 Institution of Electrical Engineers
File   6:NTIS 1964-2005/Jul W4
         (c) 2005 NTIS, Intl Cpyrght All Rights Res
File   8:Ei Compendex(R) 1970-2005/Jul W4
         (c) 2005 Elsevier Eng.  Info. Inc.
File  34:SciSearch(R) Cited Ref Sci 1990-2005/Jul W4
         (c) 2005 Inst for Sci Info
File  35:Dissertation Abs Online 1861-2005/Jul
         (c) 2005 ProQuest Info&Learning
File  62:SPIN(R) 1975-2005/May W3
         (c) 2005 American Institute of Physics
File  65:Inside Conferences 1993-2005/Jul W5
         (c) 2005 BLDSC all rts. reserv.
File  94:JICST-EPlus 1985-2005/Jun W2
         (c)2005 Japan Science and Tech Corp(JST)
File  95:TEME-Technology & Management 1989-2005/Jun W4
         (c) 2005 FIZ TECHNIK
File  99:Wilson Appl. Sci & Tech Abs 1983-2005/Jul
         (c) 2005 The HW Wilson Co.
File 111:TGG Natl.Newspaper Index(SM) 1979-2005/Aug 02
         (c) 2005 The Gale Group
File 144:Pascal 1973-2005/Jul W4
         (c) 2005 INIST/CNRS
File 239:Mathsci 1940-2005/Sep
         (c) 2005 American Mathematical Society
File 256:TecInfoSource 82-2005/Jun
         (c) 2005 Info.Sources Inc
File 434:SciSearch(R) Cited Ref Sci 1974-1989/Dec
         (c) 1998 Inst for Sci Info
?
```

5/3,K/1 **(Item 1 from file: 2)**
DIALOG(R)File 2:INSPEC

5571792 INSPEC Abstract Number: B9706-8310E-024, C9706-5290-010
Title: A neural network **autoassociator for induction motor failure prediction**
Author(s): Petsche, T.; Marcantonio, A.; **Darken, C.** ; Hanson, S.J.; Kuhn, G.M.; Santoso, I.
Author Affiliation: Siemens Corp. Res. Inc., Princeton, NJ, USA
Conference Title: Advances in Neural Information Processing 8. Proceedings of the 1995 Conference p.924-30
Editor(s): Touretzky, D.S.; Mozer, M.C.; Hasselmo, M.E.
Publisher: MIT Press, Cambridge, MA, USA
Publication Date: 1996 Country of Publication: USA xix+1098 pp.
ISBN: 0 262 20107 0 Material Identity Number: XX96-02161
Conference Title: Proceedings of 1995 Conference on Advances in Neural Information Processing Systems 8 (ISBN 0 262 20107 0)
Conference Date: 27-30 Nov. 1995 Conference Location: Denver, CO, USA
Language: English
Subfile: B C
Copyright 1997, IEE

Title: A neural network **autoassociator for induction motor failure prediction**
Author(s): Petsche, T.; Marcantonio, A.; **Darken, C.** ; Hanson, S.J.; Kuhn, G.M.; Santoso, I.
Abstract: We present results on the use of **neural network** based autoassociators which act as novelty or anomaly detectors to detect imminent motor failures. The...
Identifiers: **neural network** autoassociator...

5/3,K/2 **(Item 2 from file: 2)**
DIALOG(R)File 2:INSPEC

5364560 INSPEC Abstract Number: C9610-6170-008
Title: VR+ AI **=intelligent environments: a synergistic approach to engineering design support**
Author(s): Darken, R.P.; **Darken, C.J.**
Author Affiliation: Naval Res. Lab., Washington, DC, USA
Journal: Proceedings of the SPIE - The International Society for Optical Engineering Conference Title: Proc. SPIE - Int. Soc. Opt. Eng. (USA) vol.2653 p.292-300
Publisher: SPIE-Int. Soc. Opt. Eng,
Publication Date: 1996 Country of Publication: USA
CODEN: PSISDG ISSN: 0277-786X
SICI: 0277-786X(1996)2653L.292:VESA;1-9
Material Identity Number: C574-96121
U.S. Copyright Clearance Center Code: 0 8194 2027 1/96/$6.00
Conference Title: Stereoscopic Displays and Virtual Reality Systems III
Conference Sponsor: SPIE; Soc. Imaging Sci. & Technol
Conference Date: 30 Jan.-2 Feb. 1996 Conference Location: San Jose, CA, USA
Language: English
Subfile: C
Copyright 1996, IEE
Title: VR+ AI **=intelligent environments: a synergistic approach to engineering design support**

Author(s): Darken, R.P.; **Darken, C.J.**

Abstract: Both VR and **AI** have the potential to be huge productivity enhancers for engineering design, and in complementary ways. VR is a visualization tool allowing users to comprehend complex spatial relationships among many variables. **AI** is an exploration tool capable of finding and exploiting relationships which are very difficult to...

...effective with few variables. Using engineering design as an example, we explore how VR and **AI** might be integrated to yield productivity gains greater than either might alone. The typical engineering...

...through design, simulation, and analysis phases. VR is used to visualize a design simulation while **AI** is used to assist in the subsequent redesign. The role of the VR subsystem is...

... engineer can describe how the design is to be improved in the next iteration. The **AI** subsystem then acts on the redesign descriptions to suggest design modifications. These suggestions are integrated...

... the user, and the redesigned system is simulated again. The synthesis between the VR and **AI** subsystems results in a closed loop design system capable of effectively undertaking complex engineering design...

...Identifiers: **AI** ;

5/3,K/3 (Item 3 from file: 2)

DIALOG(R)File 2:INSPEC

5009469 INSPEC Abstract Number: C9509-1230D-067

Title: Rate of approximation results motivated by robust neural network **learning**

Author(s): **Darken, C.** ; Donahue, M.; Gurvits, L.; Sontag, E.

Author Affiliation: Learning Syst. Dept., Siemens Corp. Res. Inc., Princeton, NJ, USA

Conference Title: Proceeding of the Sixth Annual ACM Conference on Computational Learning Theory p.303-9

Publisher: ACM, New York, NY, USA

Publication Date: 1993 Country of Publication: USA vi+463 pp.

ISBN: 0 89791 611 5

U.S. Copyright Clearance Center Code: 0 89791 611 5/93/0007/0303$1.50

Conference Title: Proceedings of COLT '93. 6th ACM Conference on Computational Learning Theory

Conference Sponsor: ACM

Conference Date: 26-28 July 1993 Conference Location: Santa Cruz, CA, USA

Language: English

Subfile: C

Copyright 1995, IEE

Title: Rate of approximation results motivated by robust neural network **learning**

Author(s): **Darken, C.** ; Donahue, M.; Gurvits, L.; Sontag, E.

Abstract: The set of functions which a single hidden-layer **neural network** can approximate is increasingly well understood, yet our knowledge of how the approximation error depends...

...Identifiers: robust **neural network** learning...

...single hidden-layer **neural network** ;

5/3,K/4 (Item 4 from file: 2)
DIALOG(R)File 2:INSPEC

4533949 INSPEC Abstract Number: C9401-1230-058
Title: Learning rate schedules for faster stochastic gradient search
Author(s): **Darken, C.** ; Chang, J.; Moody, J.
Author Affiliation: Yale Univ., New Haven, CT, USA
Conference Title: Neural Networks for Signal Processing II. Proceedings of the IEEE-SP Workshop (Cat. No.92TH0430-9) p.3-12
Publisher: IEEE, New York, NY, USA
Publication Date: 1992 Country of Publication: USA 618 pp.
ISBN: 0 7803 0557 4
U.S. Copyright Clearance Center Code: 0 7803 0557 4/92/$3.00
Conference Sponsor: IEEE; Danish Comput. Neural Network Center; Tech. Univ. Denmark
Conference Date: 31 Aug.-2 Sept. 1992 Conference Location: Helsingoer, Denmark
Language: English
Subfile: C

Author(s): **Darken, C.** ; Chang, J.; Moody, J.
...Descriptors: learning (**artificial intelligence**);

5/3,K/5 (Item 5 from file: 2)
DIALOG(R)File 2:INSPEC

03960443 INSPEC Abstract Number: A91118620
Title: Neural network **and conventional classifiers for fluorescence-guided laser angioplasty**
Author(s): Gindi, G.R.; **Darken, C.J.** ; O'Brien, K.M.; Stetz, M.L.; Deckelbaum, L.I.
Author Affiliation: Yale Univ., New Haven, CT, USA
Journal: IEEE Transactions on Biomedical Engineering vol.38, no.3 p.246-52
Publication Date: March 1991 Country of Publication: USA
CODEN: IEBEAX ISSN: 0018-9294
U.S. Copyright Clearance Center Code: 0018-9294/91/0300-0246$01.00
Language: English
Subfile: A

Title: Neural network **and conventional classifiers for fluorescence-guided laser angioplasty**
Author(s): Gindi, G.R.; **Darken, C.J.** ; O'Brien, K.M.; Stetz, M.L.; Deckelbaum, L.I.
...Identifiers: **neural network** classifiers

5/3,K/6 (Item 1 from file: 8)
DIALOG(R)File 8:Ei Compendex(R)

04512361 E.I. No: EIP96063217501
Title: VR plus AI **equals intelligent environments: a synergistic approach to engineering design support**
Author: Darken, Rudolph P.; **Darken, Christian J.**
Corporate Source: Naval Research Lab., Washington, DC, USA
Conference Title: Stereoscopic Displays and Virtual Reality Systems III

Conference Location: San Jose, CA, USA Conference Date: 19960130-19960201
E.I. Conference No.: 22545
Source: Proceedings of SPIE - The International Society for Optical Engineering v 2653 1996. Society of Photo-Optical Instrumentation Engineers, Bellingham, WA, USA. p 292-300
Publication Year: 1996
CODEN: PSISDG ISSN: 0277-786X ISBN: 0-8194-2027-1
Language: English

Title: VR plus AI **equals intelligent environments: a synergistic approach to engineering design support**
Author: Darken, Rudolph P.; **Darken, Christian J.**
Abstract: Both VR and **AI** have the potential to be huge productivity enhancers for engineering design, and in complementary ways. VR is a visualization tool allowing users to comprehend complex spatial relationships among many variables. **AI** is an exploration tool capable of finding and exploiting relationships which are very difficult to...

...effective with few variables. Using engineering design as an example, we explore how VR and **AI** might be integrated to yield productivity gains greater than either might alone. The typical engineering...

...through design, simulation, and analysis phases. VR is used to visualize a design simulation while **AI** is used to assist in the subsequent redesign. The role of the VR subsystem is...

...engineer can describe how the design is to be improved in the next iteration. The **AI** subsystem then acts on the redesign descriptions to suggest design modifications. These suggestions are integrated...

...the user, and the redesigned system is simulated again. The synthesis between the VR and **AI** subsystems results in a closed loop design system capable of effectively undertaking complex engineering design...
Descriptors: *Virtual reality; **Artificial intelligence** ; Computer aided design; Visualization; Production control; Computer simulation; Data processing; Diagnosis

5/3,K/7 (Item 1 from file: 34)
DIALOG(R)File 34:SciSearch(R) Cited Ref Sci

05684162 Genuine Article#: WQ220 No. References: 28
Title: Rates of convex approximation in non-Hilbert spaces
Author(s): Donahue MJ (REPRINT) ; Gurvits L; **Darken C** ; Sontag E
Corporate Source: UNIV MINNESOTA,INST MATH & APPLICAT/MINNEAPOLIS//MN/55455 (REPRINT); SIEMENS CORP RES INC,LEARNING SYST DEPT/PRINCETON//NJ/08540; NEC RES INST,/PRINCETON//NJ/08540; RUTGERS STATE UNIV,DEPT MATH/NEW BRUNSWICK//NJ/08903
Journal: CONSTRUCTIVE APPROXIMATION, 1997, V13, N2, P187-220
ISSN: 0176-4276 Publication date: 19970000
Publisher: SPRINGER VERLAG, 175 FIFTH AVE, NEW YORK, NY 10010
Language: English Document Type: ARTICLE (ABSTRACT AVAILABLE)

Author(s): Donahue MJ (REPRINT) ; Gurvits L; **Darken C** ; Sontag E
...Abstract: p = 2.

One motivation for the questions studied here arises from the area of ''artificial **neural networks** ,'' where the problem can be stated

in terms of the growth in the number of...

5/3,K/8 (Item 2 from file: 34)
DIALOG(R)File 34:SciSearch(R) Cited Ref Sci

03177375 Genuine Article#: NK409 No. References: 106
Title: NEURAL NETWORKS **AND RELATED METHODS FOR CLASSIFICATION - DISCUSSION**
Author(s): WHITTLE P; KAY J; HAND DJ; TARASSENKO L; BROWN PJ; TITTERINGTON DM; TAYLOR C; GILKS WR; CRITCHLEY F; MAYNE AJ; WAHBA G; LUTTRELL SP; BACZKOWSKI AJ; MARDIA KV; BREIMAN L; BUNTINE W; CHATFIELD C; DEVEAUX RD ; **DARKEN CJ** ; UNGAR LH; GLENDINNING RH; HASTIE T; TIBSHIRANI R; MCLACHLAN GJ; MICHIE D; OWEN AB; WOLPERT DH; RIPLEY BD
Corporate Source: UNIV CAMBRIDGE/CAMBRIDGE//ENGLAND/; UNIV EDINBURGH/EDINBURGH EH8 9YL/MIDLOTHIAN/SCOTLAND/; TURING INST/GLASGOW//SCOTLAND/; SANTA FE INST/SANTA FE//NM/00000; UNIV OXFORD,DEPT STAT/OXFORD OX1 3TG//ENGLAND/; PRINCETON UNIV/PRINCETON//NJ/08544; SIEMENS CORP/PRINCETON//NJ/00000; UNIV STIRLING/STIRLING FK9 4LA//SCOTLAND/; OPEN UNIV/MILTON KEYNES MK7 6AA/BUCKS/ENGLAND/; UNIV TORONTO/TORONTO M5S 1A1/ONTARIO/CANADA/; UNIV QUEENSLAND/ST LUCIA/QLD 4067/AUSTRALIA/; UNIV LIVERPOOL/LIVERPOOL L69 3BX//ENGLAND/; UNIV GLASGOW/GLASGOW G12 8QQ//SCOTLAND/; UNIV LEEDS/LEEDS LS2 9JT/W YORKSHIRE/ENGLAND/; STANFORD UNIV/STANFORD//CA/94305; MRC,BIOSTAT UNIT/CAMBRIDGE//ENGLAND/; UNIV BIRMINGHAM/BIRMINGHAM B15 2TT/W MIDLANDS/ENGLAND/; UNIV WISCONSIN/MADISON//WI/53706; UNIV CALIF BERKELEY/BERKELEY//CA/94720; UNIV PENN/PHILADELPHIA//PA/19104; AT&T BELL LABS/MURRAY HILL//NJ/07974; DEF RES AGCY/MALVERN//PA/00000; RES INST ADV COMP SCI/MOFFETT FIELD//CA/00000; UNIV BATH/BATH BA2 7AY/AVON/ENGLAND/
Journal: JOURNAL OF THE ROYAL STATISTICAL SOCIETY SERIES B-METHODOLOGICAL, 1994, V56, N3, P437-456
ISSN: 0035-9246
Language: ENGLISH Document Type: DISCUSSION

Title: NEURAL NETWORKS **AND RELATED METHODS FOR CLASSIFICATION - DISCUSSION**
...Author(s): G; LUTTRELL SP; BACZKOWSKI AJ; MARDIA KV; BREIMAN L; BUNTINE W; CHATFIELD C; DEVEAUX RD; **DARKEN CJ** ; UNGAR LH; GLENDINNING RH; HASTIE T; TIBSHIRANI R; MCLACHLAN GJ; MICHIE D; OWEN AB...
Research Fronts: 92-0349 001 (**NEURAL NETWORK** BASED IMAGE COMPRESSION SYSTEM; VECTOR QUANTIZER DESIGN; ARITHMETIC CODING)
92-1210 001 (NUREG-1150 PROBABILISTIC...

...IN IMAGES; NONLINEAR DIFFUSION; TEXTURE CLASSIFICATION USING QMF BANK-BASED SUBBAND DECOMPOSITION)
92-7198 001 (**NEURAL NETWORKS** ; LEARNING ALGORITHM; PRINCIPAL COMPONENTS OF NATURAL IMAGES)

5/3,K/9 (Item 1 from file: 65)
DIALOG(R)File 65:Inside Conferences

02482824 INSIDE CONFERENCE ITEM ID: CN025919646
Why Experimentation can be better than "Perfect Guidance"
Scheffer, T.; Greiner, R.; **Darken, C.**
CONFERENCE: Machine learning-International conference; 14th
MACHINE LEARNING -INTERNATIONAL WORKSHOP THEN CONFERENCE-, 1997; CONF 14

P: 331-339
Morgan Kaufmann, 1997
ISSN: 1049-1910 ISBN: 1558604863
LANGUAGE: English DOCUMENT TYPE: Conference Papers
CONFERENCE EDITOR(S): Fisher, D. H.
CONFERENCE LOCATION: Nashville, TN
CONFERENCE DATE: Jul 1997 (199707) (199707)
NOTE:
Described as proceedings. Also known as ICML'97

Scheffer, T.; Greiner, R.; **Darken, C.**
DESCRIPTORS: **machine learning** ; ICML

5/3,K/10 (Item 1 from file: 144)
DIALOG(R)File 144:Pascal

12155601 PASCAL No.: 95-0312191
Neural networks **and related methods for classification. Discussion. Reply**
RIPLEY B D; WHITTLE P comment; KAY J comment; HAND D J comment; TARASSENKO L comment; BROWN P J comment; TITTERINGTON D M comment; TAYLOR C comment; GILKS W R comment; CRITCHEY F comment; MAYNE A J comment; WAHBA G comment; LUTTRELL S P comment; BACZKOWSKI A J comment; MARDIA K V comment; BREIMAN L comment; BUNTINE W comment; CHATFIELD C comment; DE VEAUX R D comment; **DARKEN C J** comment; UNGAR L H comment; GLENDINNING R H comment; HASTIE T comment; MCLACHLAN G J comment; MICHIE D comment; OWEN A B comment ; WOLPERT D H comment
Univ. Oxford, Oxford OX1 3TG, United Kingdom
Journal: Journal of the Royal Statistical Society. Series B. Methodological, 1994, 56 (3) 409-456
Language: English

Neural networks **and related methods for classification. Discussion. Reply**
...comment; BREIMAN L comment; BUNTINE W comment; CHATFIELD C comment; DE VEAUX R D comment; **DARKEN C J** comment; UNGAR L H comment; GLENDINNING R H comment; HASTIE T comment; MCLACHLAN...

5/3,K/11 (Item 1 from file: 239)
DIALOG(R)File 239:Mathsci

03626312 MR 2005a#82056
Noise sustained patterns.
Fluctuations and nonlinearities.
Loecher, Markus (Siemens Corporate Research, Inc., Princeton, New Jersey, 08540
Corporate Source Codes: 1-SMR
Publ: World Scientific Publishing Co., Inc., River Edge, NJ, 2003, xiv+238 pp. ISBN: 981-02-4676-5
Series: World Scientific Lecture Notes in Physics, 70.
Language: English
Subfile: MR (Mathematical Reviews) AMS
Abstract Length: LONG (26 lines)
Reviewer: Passot, Thierry (F-ODCA)

Loecher, Markus ...

...and information theoretic measures are reviewed in contexts directly applicable to biophysical processes such as **neural networks**. This book reports on many numerical simulations of model equations as well as experiments, many...

```
Set     Items   Description
S1         17   AU=(DARKEN C? OR DARKEN, C? OR LOECHER M? OR LOECHER, M? OR
                 LOCHER M? OR LOCHER, M?)
S2        106   CHRIS?(2N)DARKEN OR MARK?(2N)(LOCHER OR LOECHER)
S3     242961   NEURAL()NETWORK? OR VIRTUAL()AGE OR RADIAL()BIAS OR RBF OR
             BIAS()FUNCTION? OR WEAR?()INCREMENT? OR ARTIFICIAL()INTELLIG?
             OR AI OR MACHINE?()LEARN?
S4          1   S1:S2 AND S3
File   9:Business & Industry(R) Jul/1994-2005/Aug 02
         (c) 2005  The Gale Group
File  13:BAMP 2005/Jul W4
         (c) 2005  The Gale Group
File  15:ABI/Inform(R) 1971-2005/Aug 03
         (c) 2005 ProQuest Info&Learning
File  16:Gale Group PROMT(R) 1990-2005/Aug 02
         (c) 2005 The Gale Group
File  20:Dialog Global Reporter 1997-2005/Aug 03
         (c) 2005 Dialog
File  47:Gale Group Magazine DB(TM) 1959-2005/Aug 03
         (c) 2005 The Gale group
File  75:TGG Management Contents(R) 86-2005/Jul W4
         (c) 2005 The Gale Group
File  88:Gale Group Business A.R.T.S. 1976-2005/Aug 02
         (c) 2005 The Gale Group
File  98:General Sci Abs/Full-Text 1984-2004/Dec
         (c) 2005 The HW Wilson Co.
File 141:Readers Guide 1983-2004/Dec
         (c) 2005 The HW Wilson Co
File 148:Gale Group Trade & Industry DB 1976-2005/Aug 03
         (c)2005 The Gale Group
File 160:Gale Group PROMT(R) 1972-1989
         (c) 1999 The Gale Group
File 275:Gale Group Computer DB(TM) 1983-2005/Aug 03
         (c) 2005 The Gale Group
File 369:New Scientist 1994-2005/May W4
         (c) 2005 Reed Business Information Ltd.
File 370:Science 1996-1999/Jul W3
         (c) 1999 AAAS
File 484:Periodical Abs Plustext 1986-2005/Jul W5
         (c) 2005 ProQuest
File 553:Wilson Bus. Abs. FullText 1982-2004/Dec
         (c) 2005 The HW Wilson Co
File 610:Business Wire 1999-2005/Aug 03
         (c) 2005 Business Wire.
File 613:PR Newswire 1999-2005/Aug 03
         (c) 2005 PR Newswire Association Inc
File 621:Gale Group New Prod.Annou.(R) 1985-2005/Aug 03
         (c) 2005 The Gale Group
File 624:McGraw-Hill Publications 1985-2005/Aug 03
         (c) 2005 McGraw-Hill Co. Inc
File 634:San Jose Mercury  Jun 1985-2005/Aug 02
         (c) 2005 San Jose Mercury News
File 635:Business Dateline(R) 1985-2005/Aug 03
         (c) 2005 ProQuest Info&Learning
File 636:Gale Group Newsletter DB(TM) 1987-2005/Aug 02
         (c) 2005 The Gale Group
File 647:CMP  Computer Fulltext 1988-2005/Jul W3
         (c) 2005 CMP Media, LLC
File 674:Computer News Fulltext 1989-2005/Jul W5
         (c) 2005 IDG Communications
File 696:DIALOG Telecom. Newsletters 1995-2005/Aug 02
```

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         (c) 2005 Dialog
File 810:Business Wire 1986-1999/Feb 28
         (c) 1999 Business Wire
File 813:PR Newswire 1987-1999/Apr 30
         (c) 1999 PR Newswire Association Inc
?
```

4/3,K/1 (Item 1 from file: 88)
DIALOG(R)File 88:Gale Group Business A.R.T.S.

05820679 SUPPLIER NUMBER: 75950730
Efficient Reasoning.(in knowledge-based computers)
GREINER, RUSSELL; **DARKEN, CHRISTIAN** ; SANTOSO, N. IWAN
ACM Computing Surveys, 33, 1, 1
March, 2001
ISSN: 0360-0300 LANGUAGE: English RECORD TYPE: Fulltext
WORD COUNT: 17366 LINE COUNT: 01429

... **DARKEN, CHRISTIAN**
... the option of not expressing these assertions.

"Semantic Nets" and "Frame-based Systems" are alternative **artificial intelligence** representation formalisms. In hindsight, we can view much of the research in these areas as...HEDETNIEMI, S. M. 1998. Approximating MAPs for belief networks is NP-hard and other theorems. **Artificial Intelligence** 102, 21-38.

ALCHOURRON, C. E., G ARDENFORS, P., AND MAKINSON, D. 1985. On the...